In [103]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
import seaborn as sns
from warnings import filterwarnings
filterwarnings('ignore')

pd.options.display.max_columns = None
pd.options.display.max_rows = None
pd.options.display.float_format = '{:.6f}'.format

import statsmodels
import statsmodels.api as sm
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder

from sklearn import metrics
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.metrics import cohen_kappa_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve
from sklearn.metrics import accuracy_score

from sklearn.feature_selection import RFE

from sklearn.neighbors import KNeighborsClassifier

from sklearn.naive_bayes import GaussianNB

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score

from sklearn import tree
from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import StackingClassifier

from xgboost import XGBClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score, ConfusionMatrixDisplay,
precision_score,  recall_score, f1_score, classification_report, roc_curve,  auc, precision_recall_curve,
average_precision_score
```

In [104]:
```
#1
df = pd.read_csv("mushrooms.csv")
```

In [105]:
```
df.head()
```

Out[105]:

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	stalk-shape	stalk-root	stalk-surface-above-ring	stalk-surface-below-ring	stalk-color-above-ring	stalk-color-below-ring	veil-type	veil-color	n
0	p	x	s	n	t	p	f	c	n	k	e	e	s	s	w	w	p	w	
1	e	x	s	y	t	a	f	c	b	k	e	c	s	s	w	w	p	w	
2	e	b	s	w	t	l	f	c	b	n	e	c	s	s	w	w	p	w	
3	p	x	y	w	t	p	f	c	n	n	e	e	s	s	w	w	p	w	
4	e	x	s	g	f	n	f	w	b	k	t	e	s	s	w	w	p	w	

In [106]:
```
df.dtypes
```

Out[106]:
```
class                     object
cap-shape                 object
cap-surface               object
cap-color                 object
bruises                   object
odor                      object
gill-attachment           object
gill-spacing              object
gill-size                 object
gill-color                object
stalk-shape               object
stalk-root                object
stalk-surface-above-ring  object
stalk-surface-below-ring  object
stalk-color-above-ring    object
stalk-color-below-ring    object
veil-type                 object
veil-color                object
ring-number               object
ring-type                 object
spore-print-color         object
population                object
habitat                   object
dtype: object
```

In [107]:
```
#2A
num_rows = len(df)
print("Number of rows:" , num_rows)

var_types = df.dtypes.value_counts()
print("Number and type of variable: ", var_types)
```

```
Number of rows: 8124
Number and type of variable:  object    23
dtype: int64
```

In [108]:
```
#2B

df.describe()
```

Out[108]:

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	stalk-shape	stalk-root	stalk-surface-above-ring	stalk-surface-below-ring	stalk-color-above-ring	stalk-color-below-ring	veil-type	c
count	8124	8124	8124	8124	8124	8124	8124	8124	8124	8124	8124	8124	8124	8124	8124	8124	8124	8
unique	2	6	4	10	2	9	2	2	2	12	2	5	4	4	9	9	1	
top	e	x	y	n	f	n	f	c	b	b	t	b	s	s	w	w	p	
freq	4208	3656	3244	2284	4748	3528	7914	6812	5612	1728	4608	3776	5176	4936	4464	4384	8124	7

In [109]:
```
#2C
categorical_columns = df.select_dtypes(include=['object']).columns

summary = []

for column in categorical_columns:
    categories = df[column].value_counts()
    category_percentages = df[column].value_counts(normalize=True) * 100
    summary.append((column, len(categories), category_percentages))

print("Categorical Variable Summary:")
for column, num_categories, category_percentages in summary:
    print(f"\n{column}:")
    print(f"Number of categories: {num_categories}")
    print("Percentage of observations in each category:")
    print(category_percentages)
```

```
Categorical Variable Summary:

class:
Number of categories: 2
Percentage of observations in each category:
e   51.797144
p   48.202856
Name: class, dtype: float64

cap-shape:
Number of categories: 6
Percentage of observations in each category:
x   45.002462
f   38.798621
k   10.192024
b    5.563762
s    0.393895
c    0.049237
Name: cap-shape, dtype: float64
```

In [110]:
```
#3A

df.isna().sum()
```

Out[110]:
```
class                       0
cap-shape                   0
cap-surface                 0
cap-color                   0
bruises                     0
odor                        0
gill-attachment             0
gill-spacing                0
gill-size                   0
gill-color                  0
stalk-shape                 0
stalk-root                  0
stalk-surface-above-ring    0
stalk-surface-below-ring    0
stalk-color-above-ring      0
stalk-color-below-ring      0
veil-type                   0
veil-color                  0
ring-number                 0
```

In [111]:
```
categorical_columns = df.select_dtypes(include=['object']).columns

# Perform label encoding for each categorical variable
label_encoder = LabelEncoder()

for column in categorical_columns:
    df[column] = label_encoder.fit_transform(df[column])


df
```

Out[111]:

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	stalk-shape	stalk-root	stalk-surface-above-ring	stalk-surface-below-ring	stalk-color-above-ring	stalk-color-below-ring	veil-type	c
0	1	5	2	4	1	6	1	0	1	4	0	3	2	2	7	7	0	
1	0	5	2	9	1	0	1	0	0	4	0	2	2	2	7	7	0	
2	0	0	2	8	1	3	1	0	0	5	0	2	2	2	7	7	0	
3	1	5	3	8	1	6	1	0	1	5	0	3	2	2	7	7	0	
4	0	5	2	3	0	5	1	1	0	4	1	3	2	2	7	7	0	
5	0	5	3	9	1	0	1	0	0	5	0	2	2	2	7	7	0	
6	0	0	2	8	1	0	1	0	0	2	0	2	2	2	7	7	0	
7	0	0	3	8	1	3	1	0	0	5	0	2	2	2	7	7	0	
8	1	5	3	8	1	6	1	0	1	7	0	3	2	2	7	7	0	

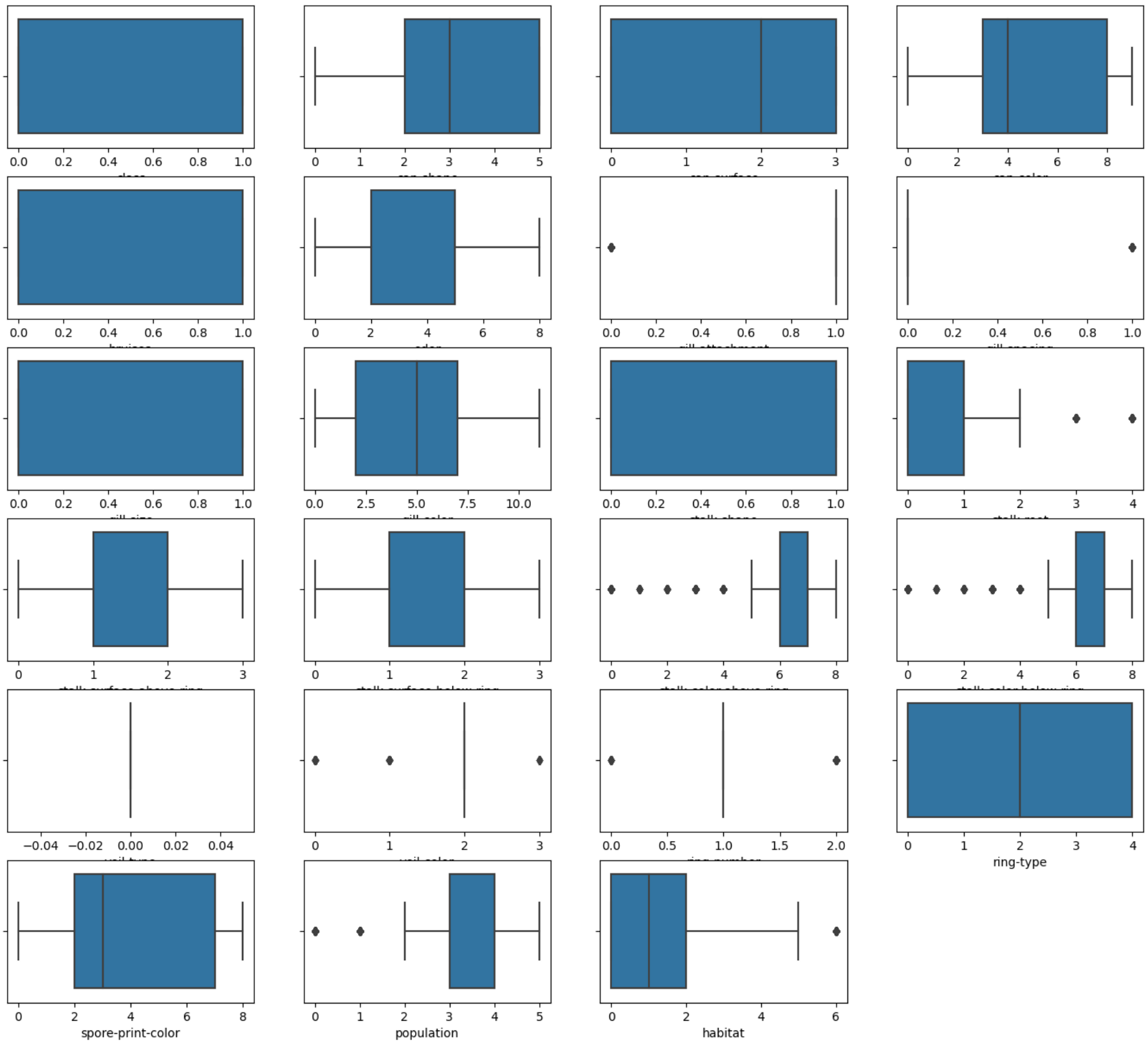
In [112]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8124 entries, 0 to 8123
Data columns (total 23 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   class                     8124 non-null   int32
 1   cap-shape                 8124 non-null   int32
 2   cap-surface               8124 non-null   int32
 3   cap-color                 8124 non-null   int32
 4   bruises                   8124 non-null   int32
 5   odor                      8124 non-null   int32
 6   gill-attachment           8124 non-null   int32
 7   gill-spacing              8124 non-null   int32
 8   gill-size                 8124 non-null   int32
 9   gill-color                8124 non-null   int32
 10  stalk-shape               8124 non-null   int32
 11  stalk-root                8124 non-null   int32
 12  stalk-surface-above-ring  8124 non-null   int32
 13  stalk-surface-below-ring  8124 non-null   int32
 14  stalk-color-above-ring    8124 non-null   int32
 15  stalk-color-below-ring    8124 non-null   int32
 16  veil-type                 8124 non-null   int32
 17  veil-color                8124 non-null   int32
 18  ring-number               8124 non-null   int32
 19  ring-type                 8124 non-null   int32
 20  spore-print-color         8124 non-null   int32
 21  population                8124 non-null   int32
 22  habitat                   8124 non-null   int32
dtypes: int32(23)
memory usage: 730.0 KB
```

In [113]:
```
df1 = df.columns
df1
```

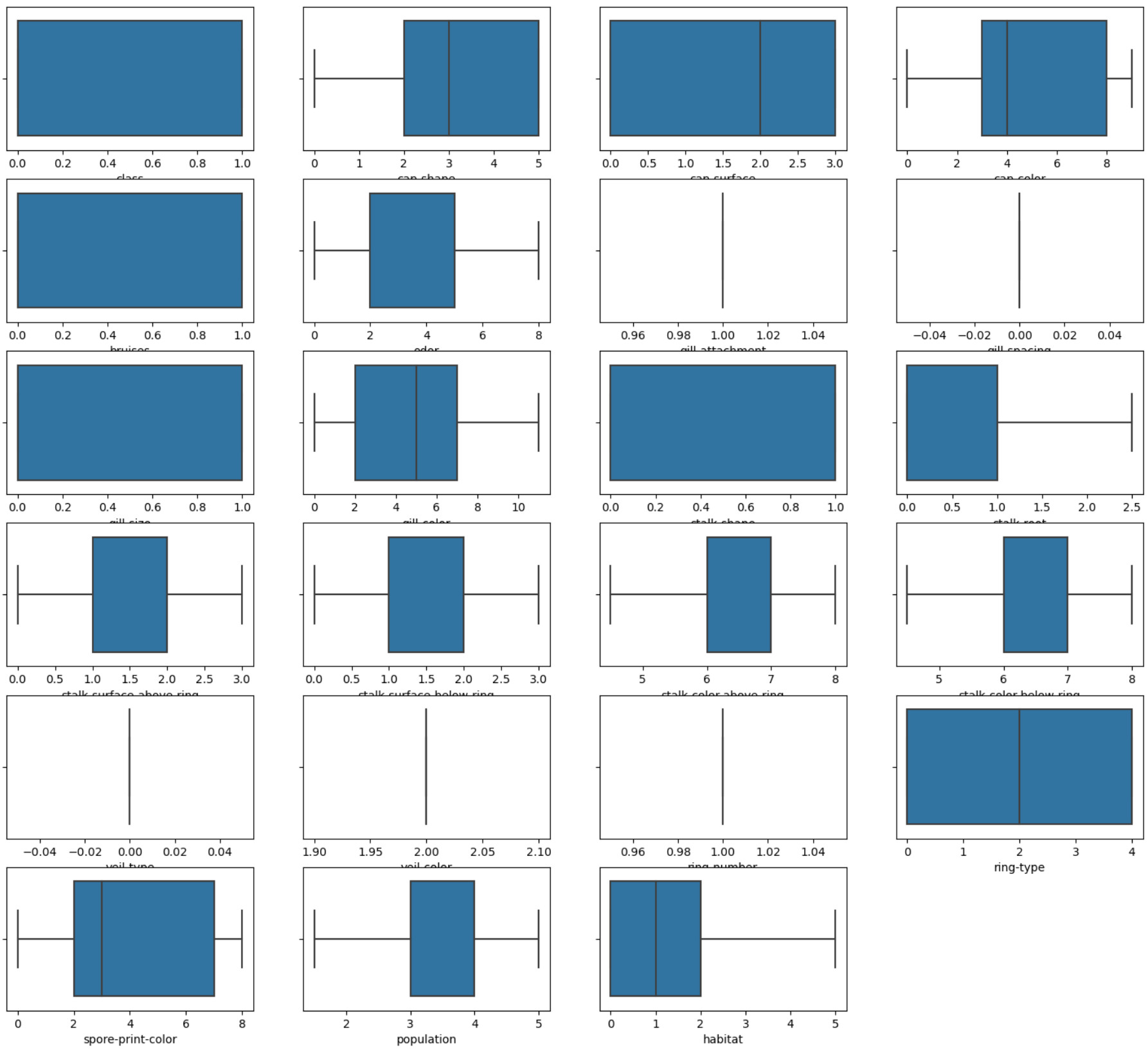
Out[113]:
```
Index(['class', 'cap-shape', 'cap-surface', 'cap-color', 'bruises', 'odor',
       'gill-attachment', 'gill-spacing', 'gill-size', 'gill-color',
       'stalk-shape', 'stalk-root', 'stalk-surface-above-ring',
       'stalk-surface-below-ring', 'stalk-color-above-ring',
       'stalk-color-below-ring', 'veil-type', 'veil-color', 'ring-number',
       'ring-type', 'spore-print-color', 'population', 'habitat'],
      dtype='object')
```

In [114]:
```
t=1
plt.figure(figsize = (17,15))
for i in df1:
    plt.subplot(6,4,t)
    sns.boxplot(df[i])
    t+=1
plt.show()
```



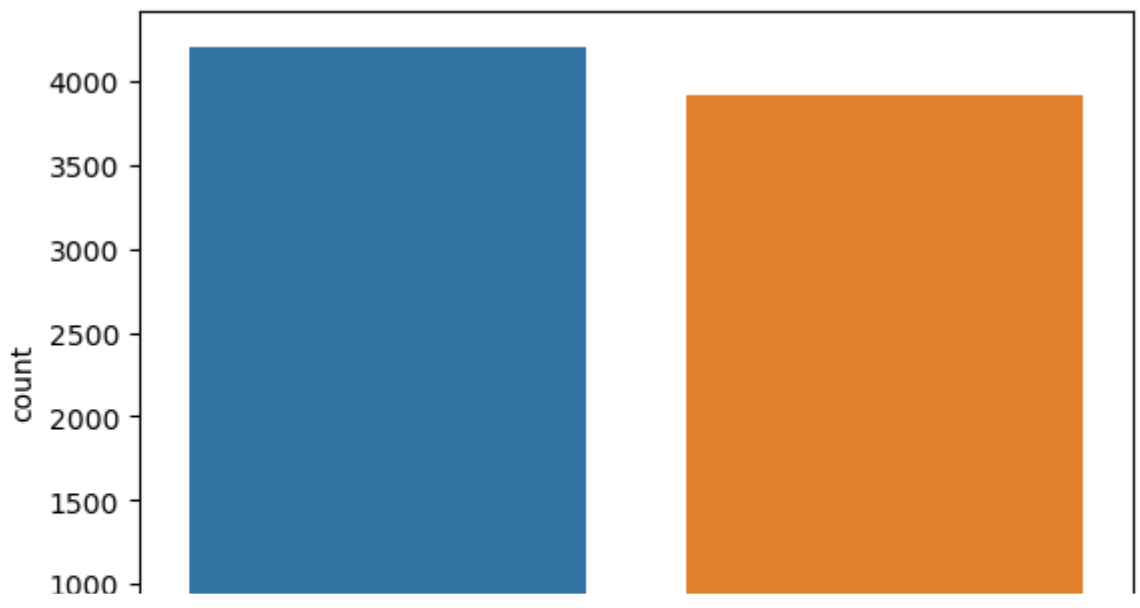
In [115]:
```
for i in df1:
    q1,q3 = np.quantile(df[i],[0.25,0.75])
    iqr = q3 - q1
    ub = q3 + (1.5 * iqr)
    lb = q1 - (1.5 * iqr)
    df[i] = np.where(df[i] > ub, ub, df[i])
    df[i] = np.where(df[i] < lb, lb, df[i])
```

In [116]:
```
t=1
plt.figure(figsize = (18,16))
for i in df1:
    plt.subplot(6,4,t)
    sns.boxplot(df[i])
    t+=1
plt.show()
```



In [118]:
```
sns.countplot(df['class'])
```

Out[118]: <AxesSubplot:xlabel='class', ylabel='count'>



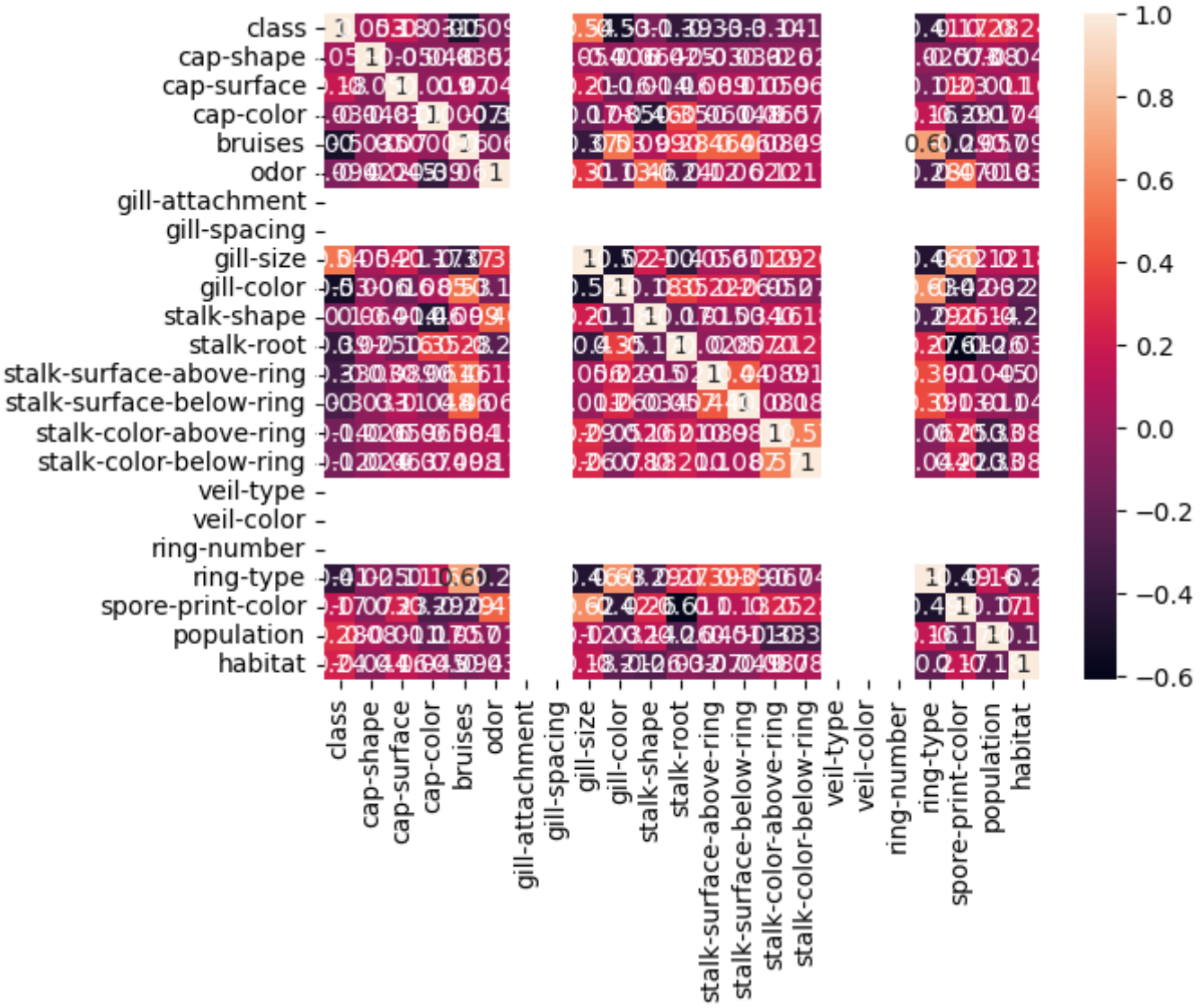
In [119]:
```
df.corr()
```

Out[119]:

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	stalk-shape	stalk-root	
class	1.000000	0.052951	0.178446	-0.031384	-0.501530	-0.093552	NaN	NaN	0.540024	-0.530566	-0.102019	-0.388292	-0
cap-shape	0.052951	1.000000	-0.050454	-0.048203	-0.035374	-0.021935	NaN	NaN	0.054050	-0.006039	0.063794	0.025086	-0
cap-surface	0.178446	-0.050454	1.000000	-0.019402	0.070228	0.045233	NaN	NaN	0.208100	-0.161017	-0.014123	-0.158140	0
cap-color	-0.031384	-0.048203	-0.019402	1.000000	-0.000764	-0.387121	NaN	NaN	-0.169464	0.084659	-0.456496	0.345921	-0
bruises	-0.501530	-0.035374	0.070228	-0.000764	1.000000	-0.061825	NaN	NaN	-0.369596	0.527120	0.099364	0.283288	0
odor	-0.093552	-0.021935	0.045233	-0.387121	-0.061825	1.000000	NaN	NaN	0.310495	-0.129213	0.459766	-0.243078	0
gill-attachment	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
gill-spacing	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

In [120]:
```
sns.heatmap(df.corr() , annot = True)
```

Out[120]: <AxesSubplot:>



In [121]:
```
dfc = df.copy()
```

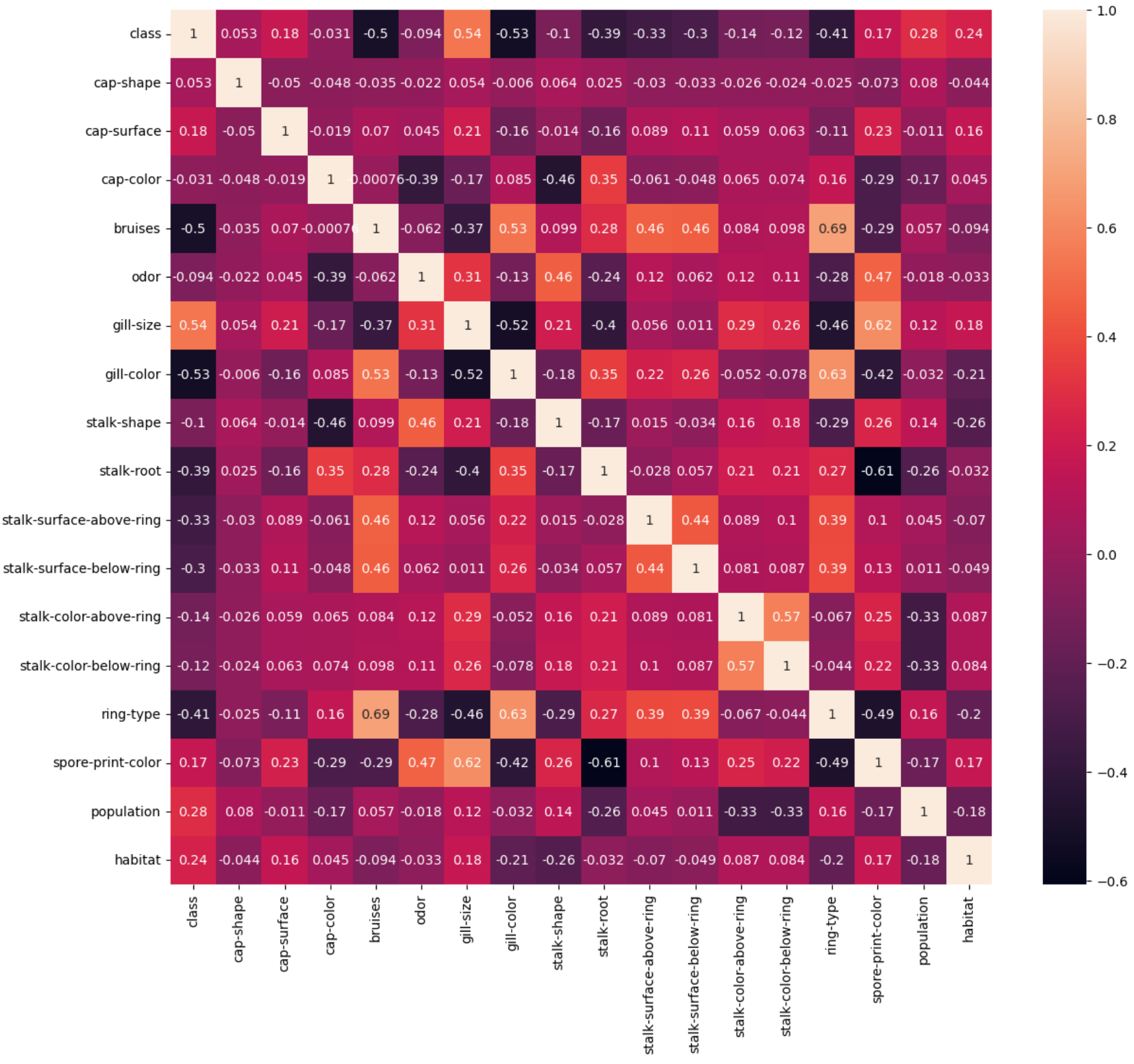
In [122]:
```
dfc = dfc.drop(['gill-attachment','gill-spacing','veil-type','veil-color','ring-number'] , axis = 1)
```

In [123]:
```
dfc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8124 entries, 0 to 8123
Data columns (total 18 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   class                     8124 non-null   float64
 1   cap-shape                 8124 non-null   float64
 2   cap-surface               8124 non-null   float64
 3   cap-color                 8124 non-null   float64
 4   bruises                   8124 non-null   float64
 5   odor                      8124 non-null   float64
 6   gill-size                 8124 non-null   float64
 7   gill-color                8124 non-null   float64
 8   stalk-shape               8124 non-null   float64
 9   stalk-root                8124 non-null   float64
 10  stalk-surface-above-ring  8124 non-null   float64
 11  stalk-surface-below-ring  8124 non-null   float64
 12  stalk-color-above-ring    8124 non-null   float64
 13  stalk-color-below-ring    8124 non-null   float64
 14  ring-type                 8124 non-null   float64
 15  spore-print-color         8124 non-null   float64
 16  population                8124 non-null   float64
 17  habitat                   8124 non-null   float64
dtypes: float64(18)
memory usage: 1.1 MB
```

In [198]:
```
plt.figure(figsize = (14,12))
sns.heatmap(dfc.corr() , annot = True)
```

Out[198]: <AxesSubplot:>



In [199]:
```
dfc.corr()
```

Out[199]:

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-size	gill-color	stalk-shape	stalk-root	stalk-surface-above-ring	stalk-surface-below-ring	st co abo
class	1.000000	0.052951	0.178446	-0.031384	-0.501530	-0.093552	0.540024	-0.530566	-0.102019	-0.388292	-0.334593	-0.298801	-0.135
cap-shape	0.052951	1.000000	-0.050454	-0.048203	-0.035374	-0.021935	0.054050	-0.006039	0.063794	0.025086	-0.030417	-0.032591	-0.026
cap-surface	0.178446	-0.050454	1.000000	-0.019402	0.070228	0.045233	0.208100	-0.161017	-0.014123	-0.158140	0.089090	0.107965	0.059
cap-color	-0.031384	-0.048203	-0.019402	1.000000	-0.000764	-0.387121	-0.169464	0.084659	-0.456496	0.345921	-0.060837	-0.047710	0.065
bruises	-0.501530	-0.035374	0.070228	-0.000764	1.000000	-0.061825	-0.369596	0.527120	0.099364	0.283288	0.460824	0.458983	0.083
odor	-0.093552	-0.021935	0.045233	-0.387121	-0.061825	1.000000	0.310495	-0.129213	0.459766	-0.243078	0.118617	0.061820	0.117
gill-size	0.540024	0.054050	0.208100	-0.169464	-0.369596	0.310495	1.000000	-0.516736	0.214576	-0.398834	0.056310	0.010894	0.289
gill-color	-0.530566	-0.006039	-0.161017	0.084659	0.527120	-0.129213	-0.516736	1.000000	-0.175699	0.352774	0.224287	0.257224	-0.052
stalk-shape	-0.102019	0.063794	-0.014123	-0.456496	0.099364	0.459766	0.214576	-0.175699	1.000000	-0.173906	0.015193	-0.034399	0.163
stalk-root	-0.388292	0.025086	-0.158140	0.345921	0.283288	-0.243078	-0.398834	0.352774	-0.173906	1.000000	-0.027988	0.057153	0.210
stalk-surface-above-ring	-0.334593	-0.030417	0.089090	-0.060837	0.460824	0.118617	0.056310	0.224287	0.015193	-0.027988	1.000000	0.437164	0.088
stalk-surface-below-ring	-0.298801	-0.032591	0.107965	-0.047710	0.458983	0.061820	0.010894	0.257224	-0.034399	0.057153	0.437164	1.000000	0.081
stalk-color-above-ring	-0.135827	-0.026404	0.059037	0.065283	0.083521	0.117665	0.289672	-0.052336	0.163874	0.210475	0.088846	0.081229	1.000
stalk-color-below-ring	-0.122912	-0.024374	0.063078	0.073875	0.097564	0.108979	0.259473	-0.077873	0.182327	0.211502	0.104292	0.087385	0.568
ring-type	-0.411771	-0.025457	-0.106407	0.162513	0.692973	-0.281387	-0.460872	0.629398	-0.291444	0.266703	0.390091	0.394644	-0.067
spore-print-color	0.171961	-0.073416	0.230364	-0.293523	-0.285008	0.469055	0.622991	-0.416135	0.258831	-0.607706	0.100764	0.130974	0.248
population	0.284947	0.079807	-0.010539	-0.172971	0.056539	-0.017907	0.122654	-0.031555	0.143931	-0.262454	0.044518	0.011279	-0.331
habitat	0.238180	-0.043509	0.161629	0.044855	-0.094463	-0.033279	0.176345	-0.212559	-0.262003	-0.031825	-0.069740	-0.049288	0.087

In [200]:
```
dfc.skew()
```

Out[200]:
```
class                      0.071946
cap-shape                 -0.247052
cap-surface               -0.590859
cap-color                  0.706965
bruises                    0.342750
odor                      -0.080790
gill-size                  0.825797
gill-color                 0.061410
stalk-shape               -0.271345
stalk-root                 0.468265
stalk-surface-above-ring  -1.098739
stalk-surface-below-ring  -0.757703
stalk-color-above-ring    -0.865085
stalk-color-below-ring    -0.815881
ring-type                 -0.290018
spore-print-color          0.548426
population                -0.819709
habitat                    0.884403
dtype: float64
```

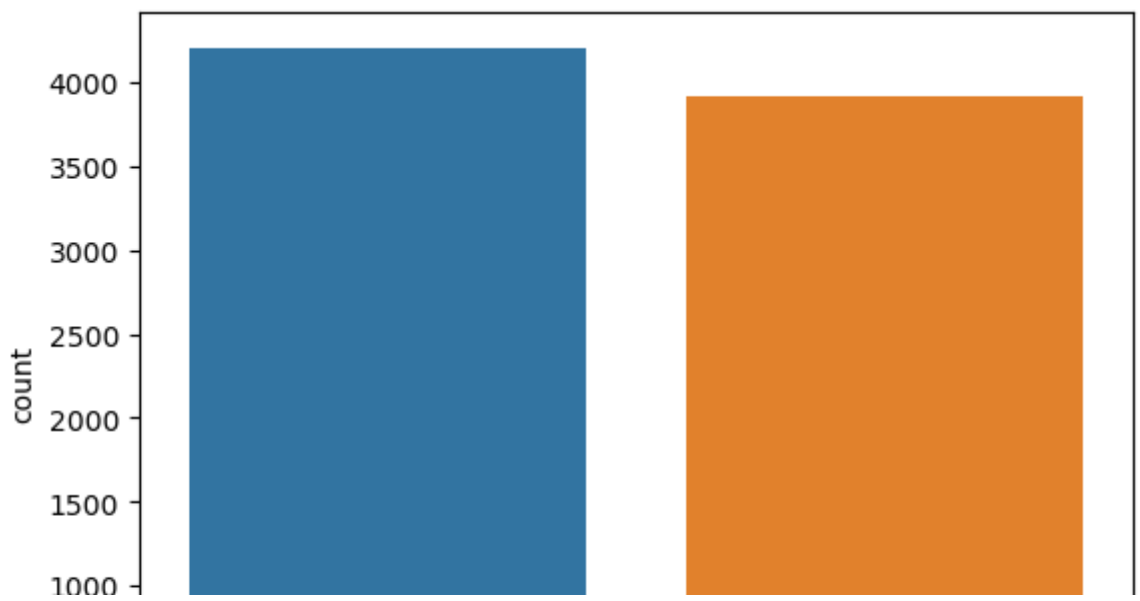
In [201]:
```
X = dfc.drop(['class'],axis=1)
y = dfc['class']
```

In [ ]:
```
X = sm.add_constant(X)
```

In [202]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=10)
```

In [203]:
```
sns.countplot(dfc['class'])
```

Out[203]: <AxesSubplot:xlabel='class', ylabel='count'>



In [204]:
```
def get_test_report(model, test_data):
    test_pred = model.predict(test_data)
    return(classification_report(y_test, test_pred))
```

In [205]:
```
def get_train_report(model, train_data):
    train_pred = model.predict(train_data)
    return(classification_report(y_train, train_pred))
```

In [206]:
```
def plot_confusion_matrix(model, test_data):
    y_pred = model.predict(test_data)
    cm = confusion_matrix(y_test, y_pred)
    conf_matrix = pd.DataFrame(data = cm,columns = ['Predicted:0','Predicted:1'], index = ['Actual:0','Actual:1'])
    sns.heatmap(conf_matrix, annot = True, fmt = 'd', cmap = ListedColormap(['lightskyblue']), cbar = False,
                linewidths = 0.1, annot_kws = {'size':25})
    plt.xticks(fontsize = 20)
    plt.yticks(fontsize = 20)
    plt.show()
```

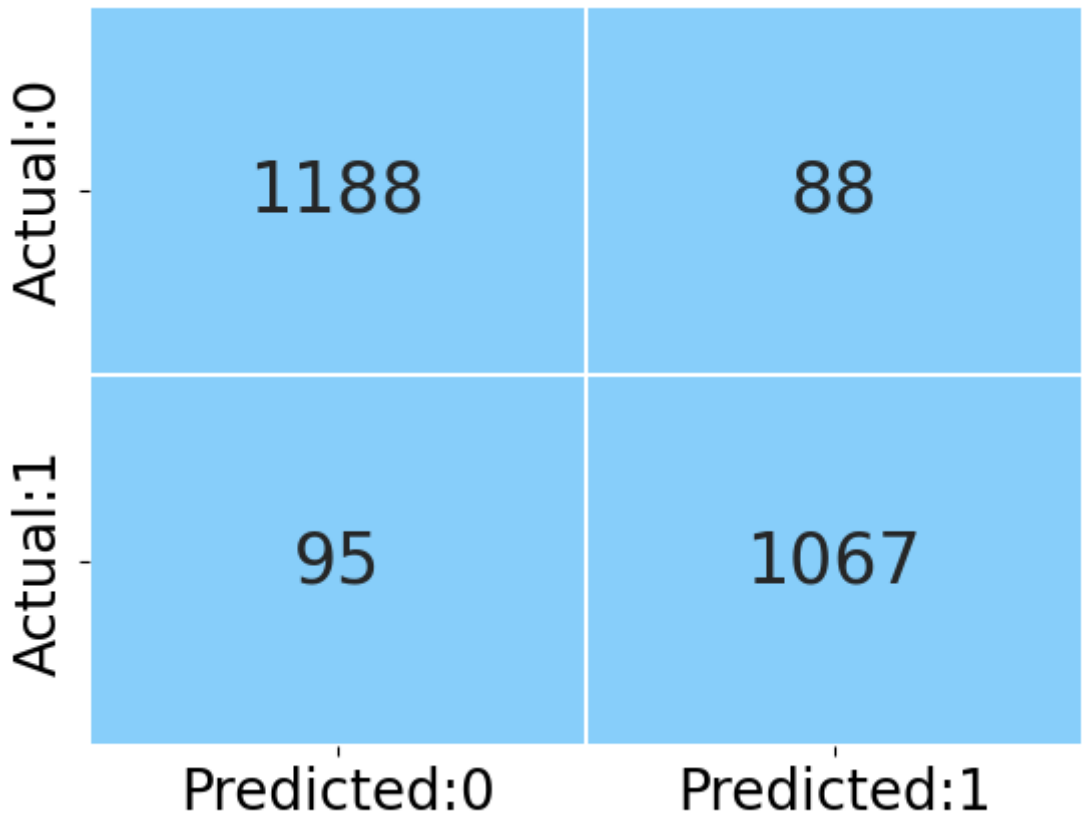
In [207]:
```
def plot_roc(model, test_data):
    y_pred_prob = model.predict_proba(test_data)[:,1]
    fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
    plt.plot(fpr, tpr)
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.0])
    plt.plot([0, 1], [0, 1],'r--')
    plt.title('ROC curve for Cancer Prediction Classifier', fontsize = 15)
    plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
    plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
    plt.text(x = 0.02, y = 0.9, s = ('AUC Score:',round(roc_auc_score(y_test, y_pred_prob),4)))
    plt.grid(True)
```

Logistic Reg

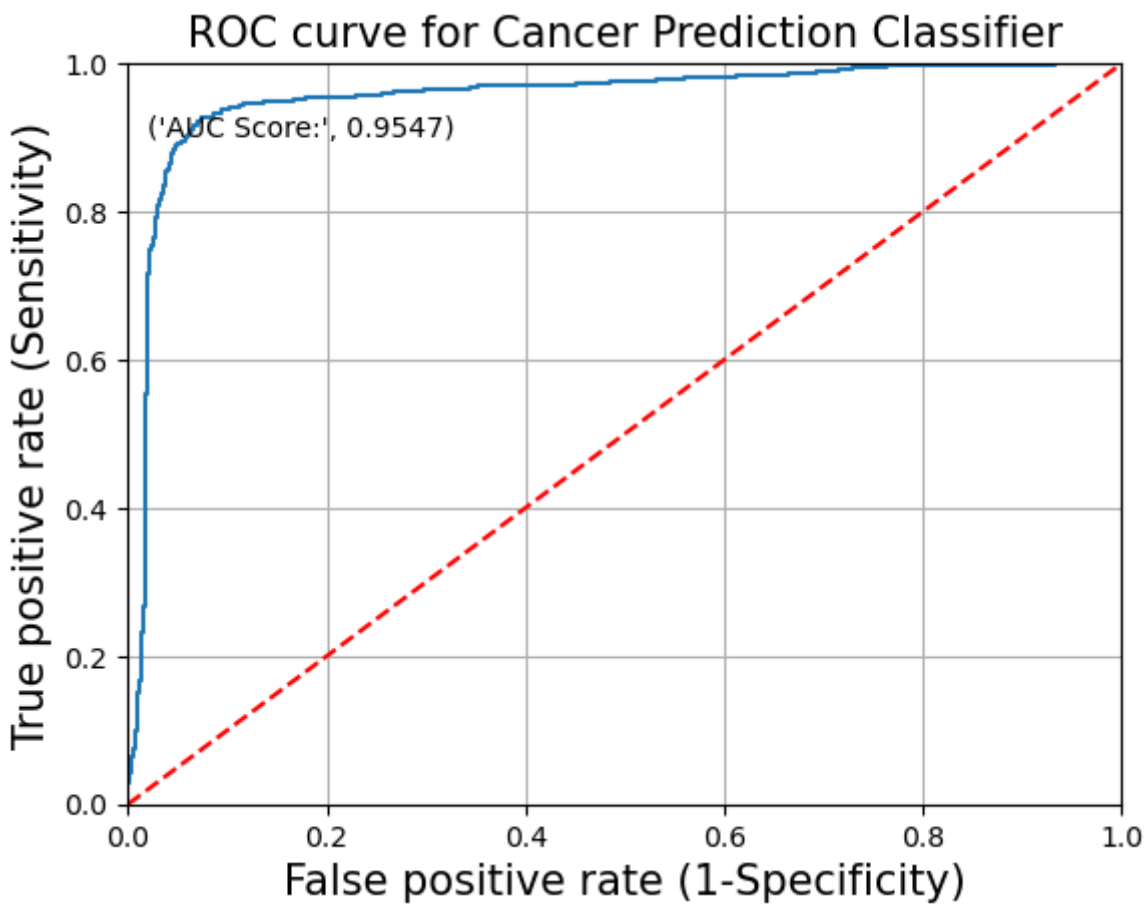
In [208]:
```
Base_model=LogisticRegression()
Base_model.fit(X_train,y_train)
```

Out[208]: LogisticRegression()

In [209]:
```
plot_confusion_matrix(Base_model, test_data = X_test)
```



In [210]:
```
plot_roc(Base_model, test_data = X_test)
```



In [211]:
```
test_report = get_test_report(Base_model, test_data = X_test)
print(test_report)
```

```
              precision    recall  f1-score   support

         0.0       0.93      0.93      0.93      1276
         1.0       0.92      0.92      0.92      1162

    accuracy                           0.92      2438
   macro avg       0.92      0.92      0.92      2438
weighted avg       0.92      0.92      0.92      2438
```

In [212]:
```
print('Classification Report for train set: \n', get_train_report(Base_model, train_data = X_train))
```

```
Classification Report for train set:
               precision    recall  f1-score   support

         0.0       0.93      0.93      0.93      2932
         1.0       0.93      0.92      0.93      2754

    accuracy                           0.93      5686
   macro avg       0.93      0.93      0.93      5686
weighted avg       0.93      0.93      0.93      5686
```

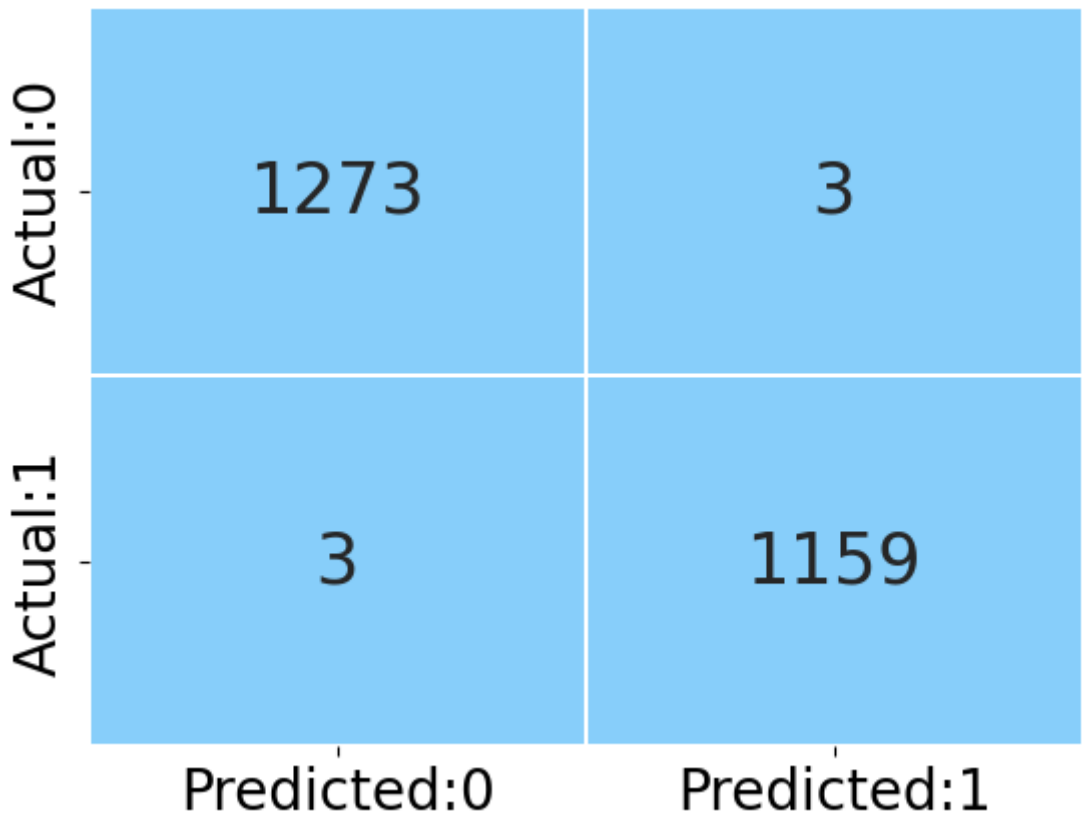
In [213]:
```
print('Classification Report for test set: \n', get_test_report(Base_model, test_data = X_test))
```

```
Classification Report for test set:
               precision    recall  f1-score   support

         0.0       0.93      0.93      0.93      1276
         1.0       0.92      0.92      0.92      1162

    accuracy                           0.92      2438
   macro avg       0.92      0.92      0.92      2438
weighted avg       0.92      0.92      0.92      2438
```

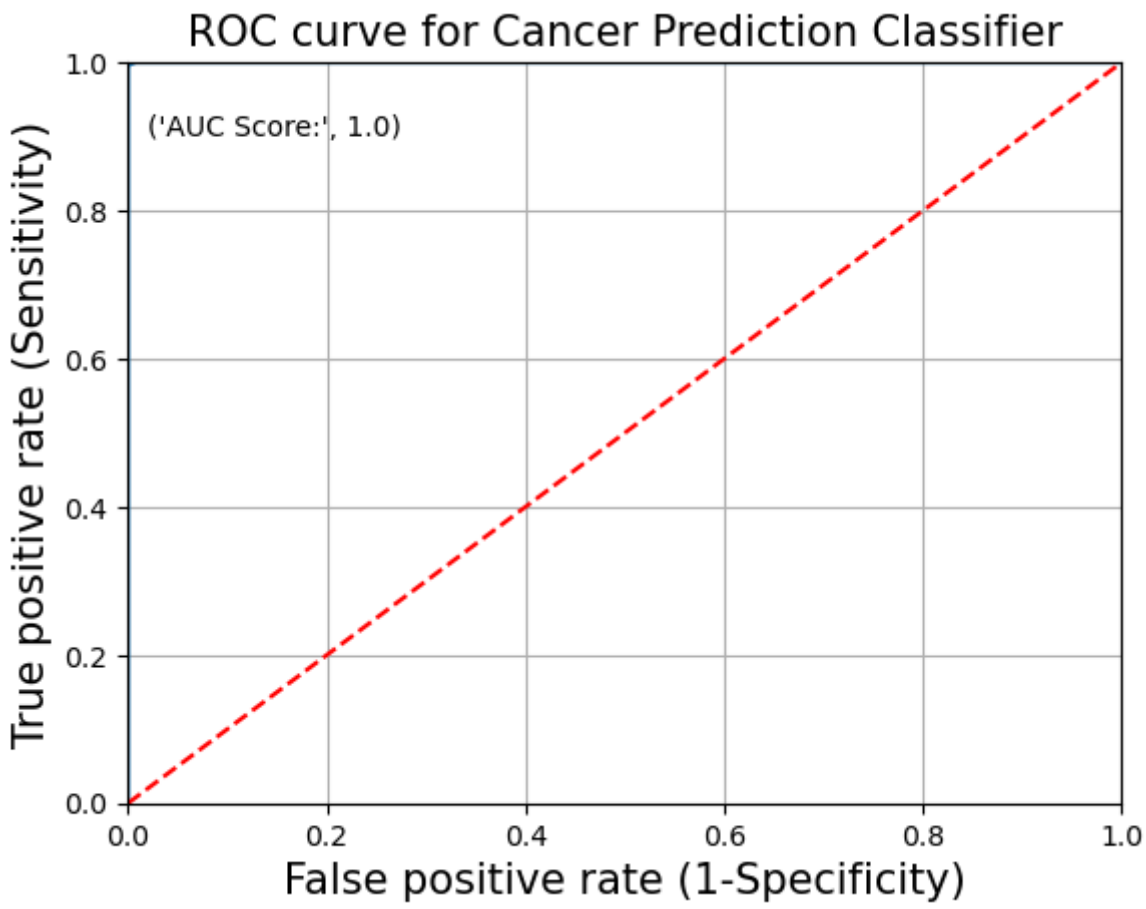
KNN

In [214]:
```
knn_classification = KNeighborsClassifier(n_neighbors = 3)
knn_model = knn_classification.fit(X_train, y_train)
```

In [215]:
```
plot_confusion_matrix(knn_model, test_data = X_test)
```



In [216]:
```
plot_roc(knn_model, test_data = X_test)
```



KNN Classification GridSearchCV

In [217]:
```
tuned_paramaters = {'n_neighbors': np.arange(1, 25, 2),
                    'metric': ['hamming','euclidean','manhattan','Chebyshev']}

# instantiate the 'KNeighborsClassifier'
knn_classification = KNeighborsClassifier()
knn_grid = GridSearchCV(estimator = knn_classification,
                        param_grid = tuned_paramaters,
                        cv = 5,
                        scoring = 'accuracy')
knn_grid.fit(X_train, y_train)
print('Best parameters for KNN Classifier: ', knn_grid.best_params_, '\n')
```

```
Best parameters for KNN Classifier:  {'metric': 'hamming', 'n_neighbors': 1}
```

In [218]:
```
knn_classification = KNeighborsClassifier(n_neighbors = 1,metric= 'manhattan')
knn_model_hp = knn_classification.fit(X_train, y_train)
```

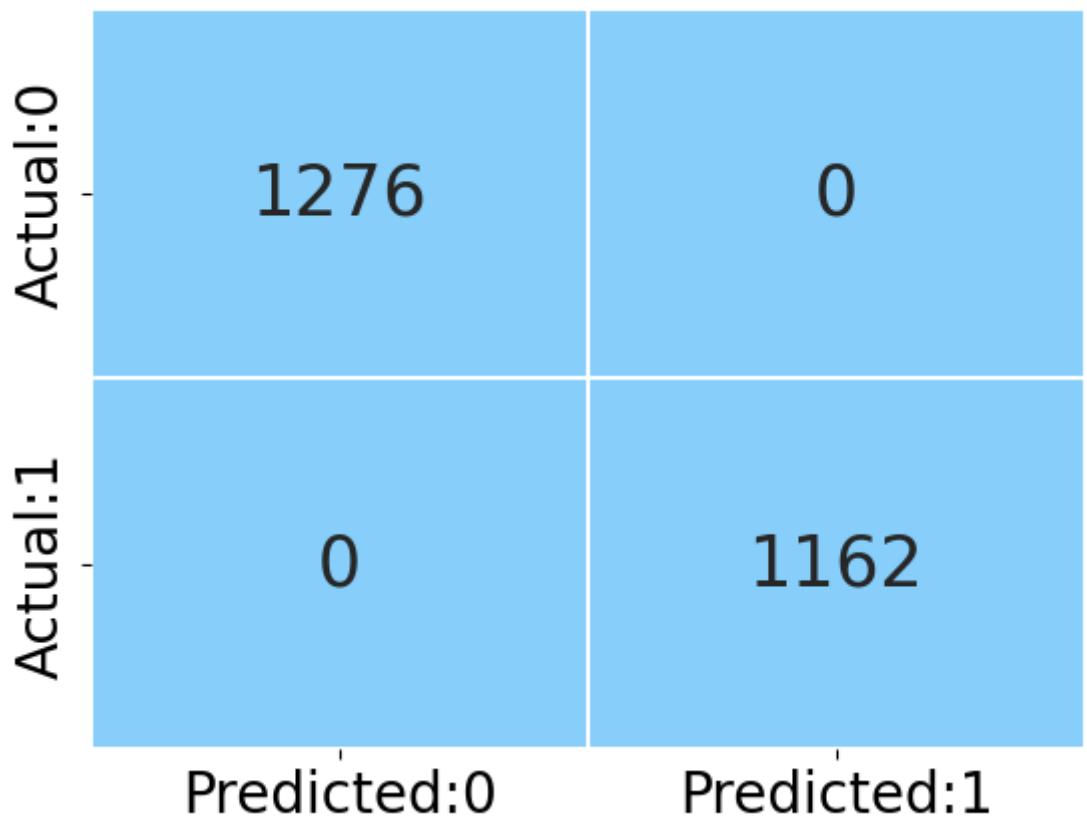
In [219]:
```
train_report = get_train_report(knn_model_hp, train_data = X_train)
print(train_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2932
         1.0       1.00      1.00      1.00      2754

    accuracy                           1.00      5686
   macro avg       1.00      1.00      1.00      5686
weighted avg       1.00      1.00      1.00      5686
```

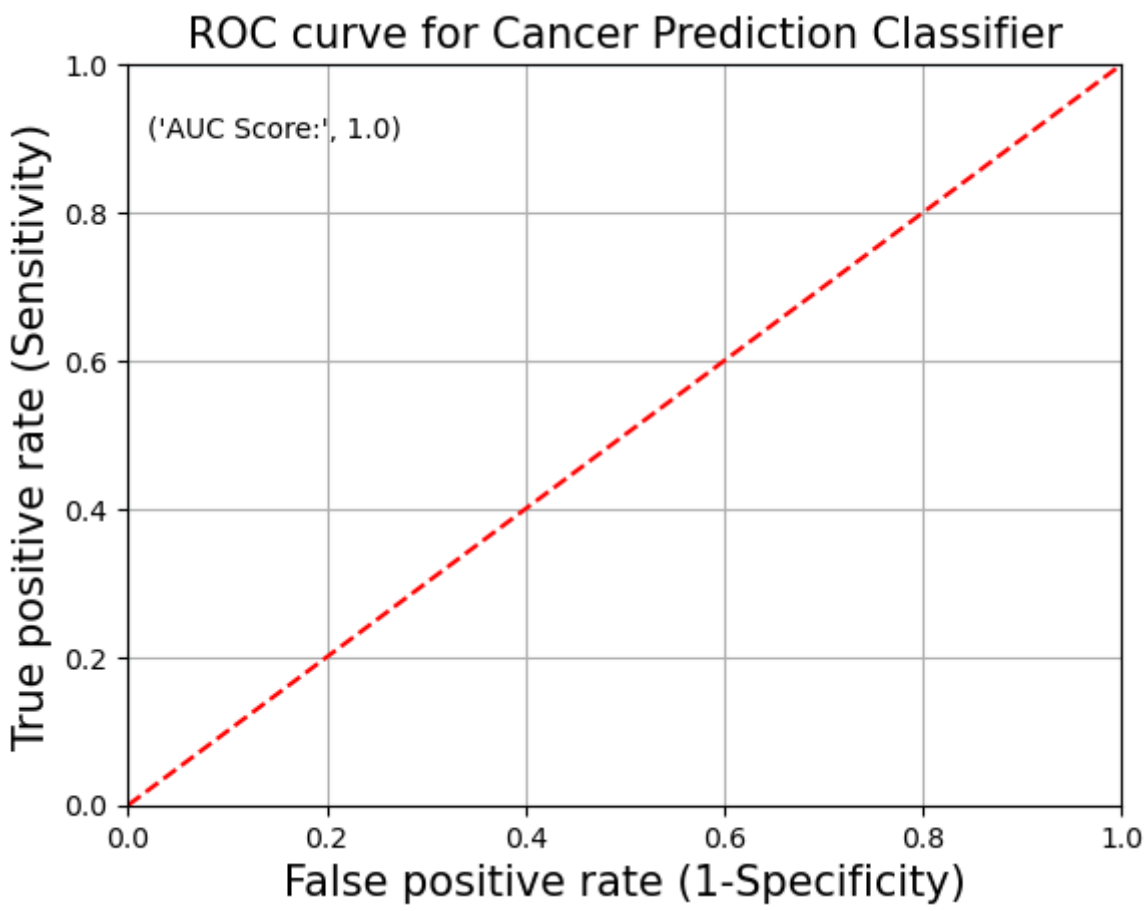
In [220]:
```
test_report = get_test_report(knn_model_hp, test_data = X_test)
print(test_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      1276
         1.0       1.00      1.00      1.00      1162

    accuracy                           1.00      2438
   macro avg       1.00      1.00      1.00      2438
weighted avg       1.00      1.00      1.00      2438
```

In [221]:
```
plot_confusion_matrix(knn_model_hp, test_data = X_test)
```



In [222]:
```
plot_roc(knn_model_hp, test_data = X_test)
```

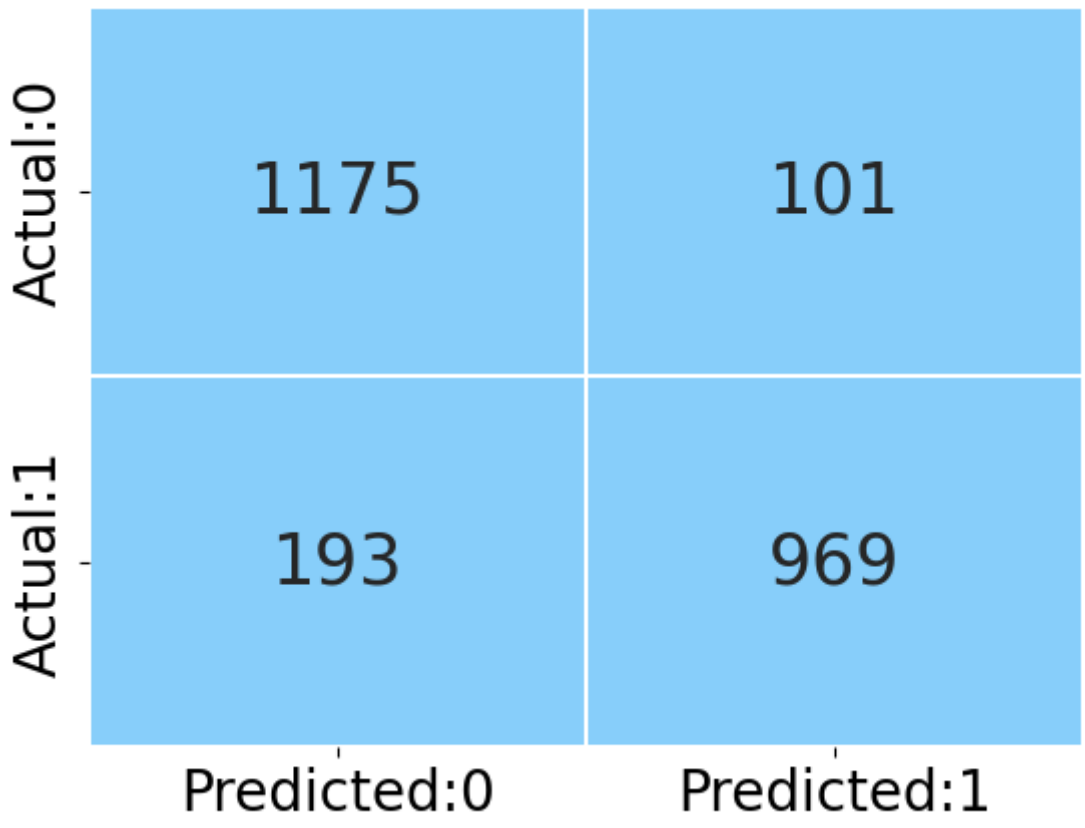


In [ ]:
```

```

GaussianNB

In [223]:
```
gnb = GaussianNB()
gnb_model = gnb.fit(X_train, y_train)
```

In [224]:
```
plot_confusion_matrix(gnb_model, test_data=X_test)
```



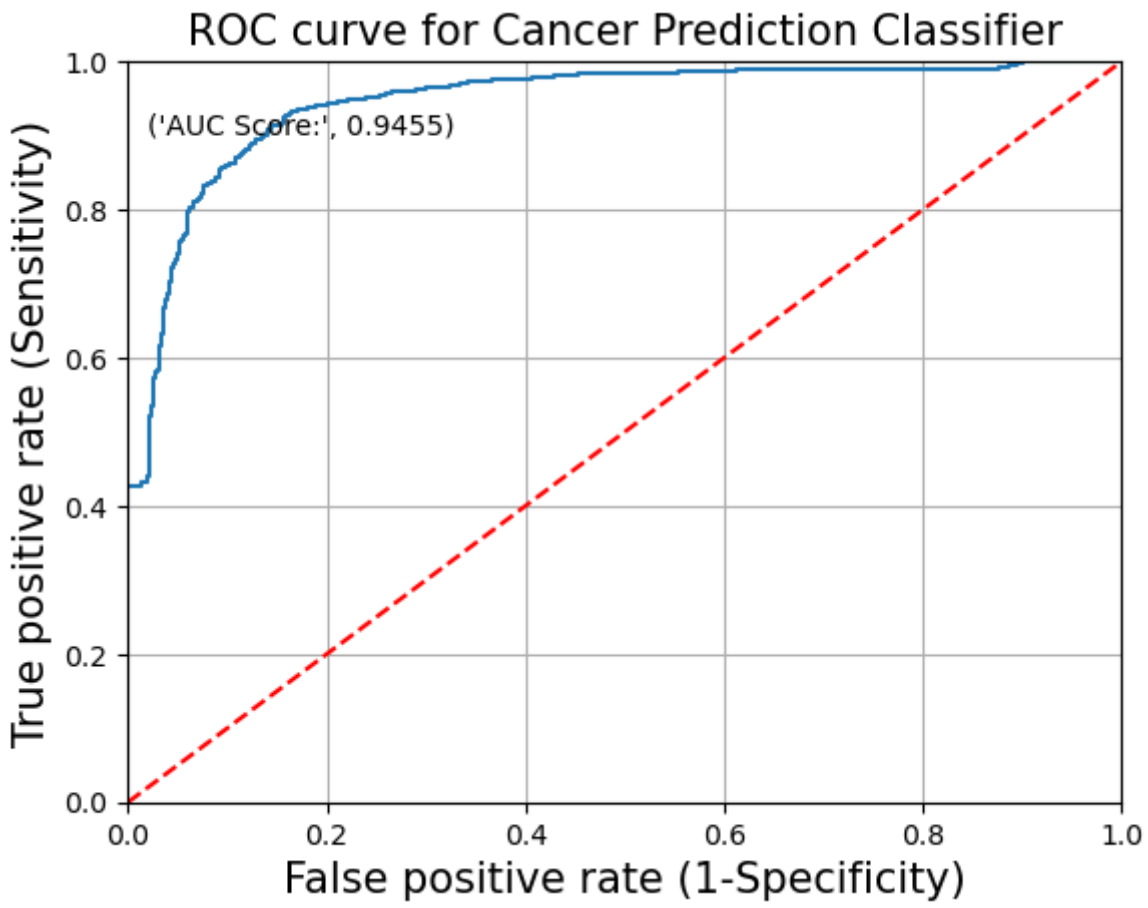
In [225]:
```
train_report = get_train_report(gnb_model, train_data=X_train)
print(train_report)
```

```
              precision    recall  f1-score   support

         0.0       0.87      0.93      0.89      2932
         1.0       0.91      0.85      0.88      2754

    accuracy                           0.89      5686
   macro avg       0.89      0.89      0.89      5686
weighted avg       0.89      0.89      0.89      5686
```

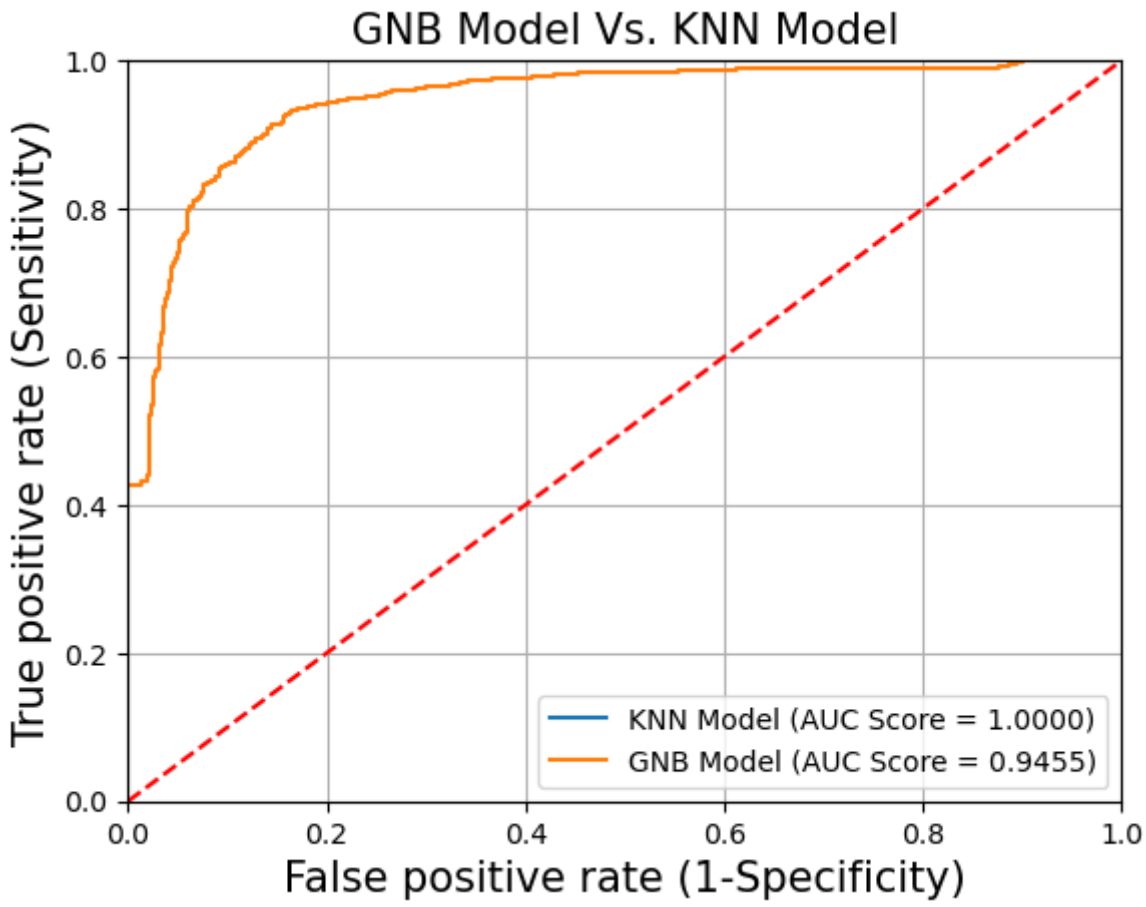
In [226]:
```
test_report = get_test_report(gnb_model, test_data=X_test)
print(test_report)
```

```
              precision    recall  f1-score   support

         0.0       0.86      0.92      0.89      1276
         1.0       0.91      0.83      0.87      1162

    accuracy                           0.88      2438
   macro avg       0.88      0.88      0.88      2438
weighted avg       0.88      0.88      0.88      2438
```

In [227]:
```
plot_roc(gnb_model, test_data=X_test)
```



In [228]:
```
y_pred_prob_knn = knn_grid.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob_knn)
auc_score_knn = roc_auc_score(y_test, y_pred_prob_knn)
plt.plot(fpr, tpr, label='KNN Model (AUC Score = %0.4f)' % auc_score_knn)
y_pred_prob_gnb = gnb_model.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob_gnb)
auc_score_gnb = roc_auc_score(y_test, y_pred_prob_gnb)
plt.plot(fpr, tpr, label='GNB Model (AUC Score = %0.4f)' % auc_score_gnb)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('GNB Model Vs. KNN Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.legend(loc = 'lower right')
plt.grid(True)
```



Decision Tree Classification

In [229]:
```
decision_tree_classification = DecisionTreeClassifier(criterion = 'entropy', random_state = 10)
decision_tree = decision_tree_classification.fit(X_train, y_train)
```

In [230]:
```
train_report = get_train_report(decision_tree, train_data=X_train)
print(train_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2932
         1.0       1.00      1.00      1.00      2754

    accuracy                           1.00      5686
   macro avg       1.00      1.00      1.00      5686
weighted avg       1.00      1.00      1.00      5686
```

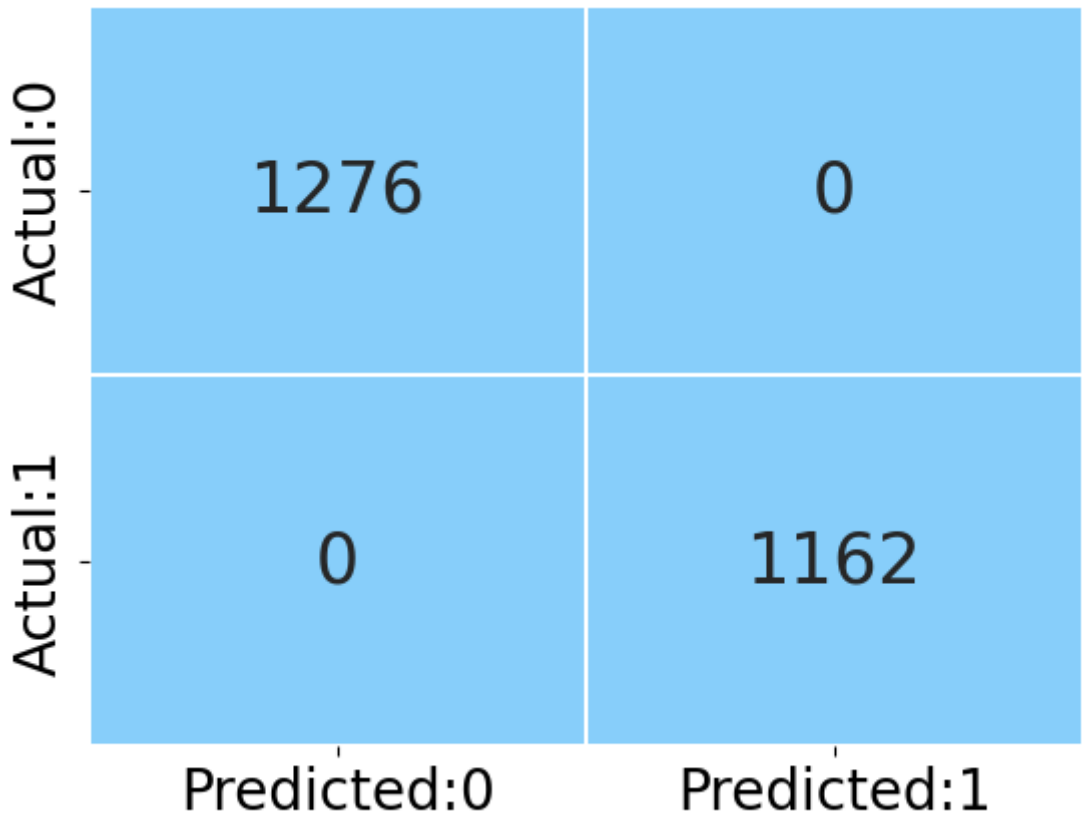
In [231]:
```
test_report = get_test_report(decision_tree, test_data=X_test)
print(test_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      1276
         1.0       1.00      1.00      1.00      1162

    accuracy                           1.00      2438
   macro avg       1.00      1.00      1.00      2438
weighted avg       1.00      1.00      1.00      2438
```

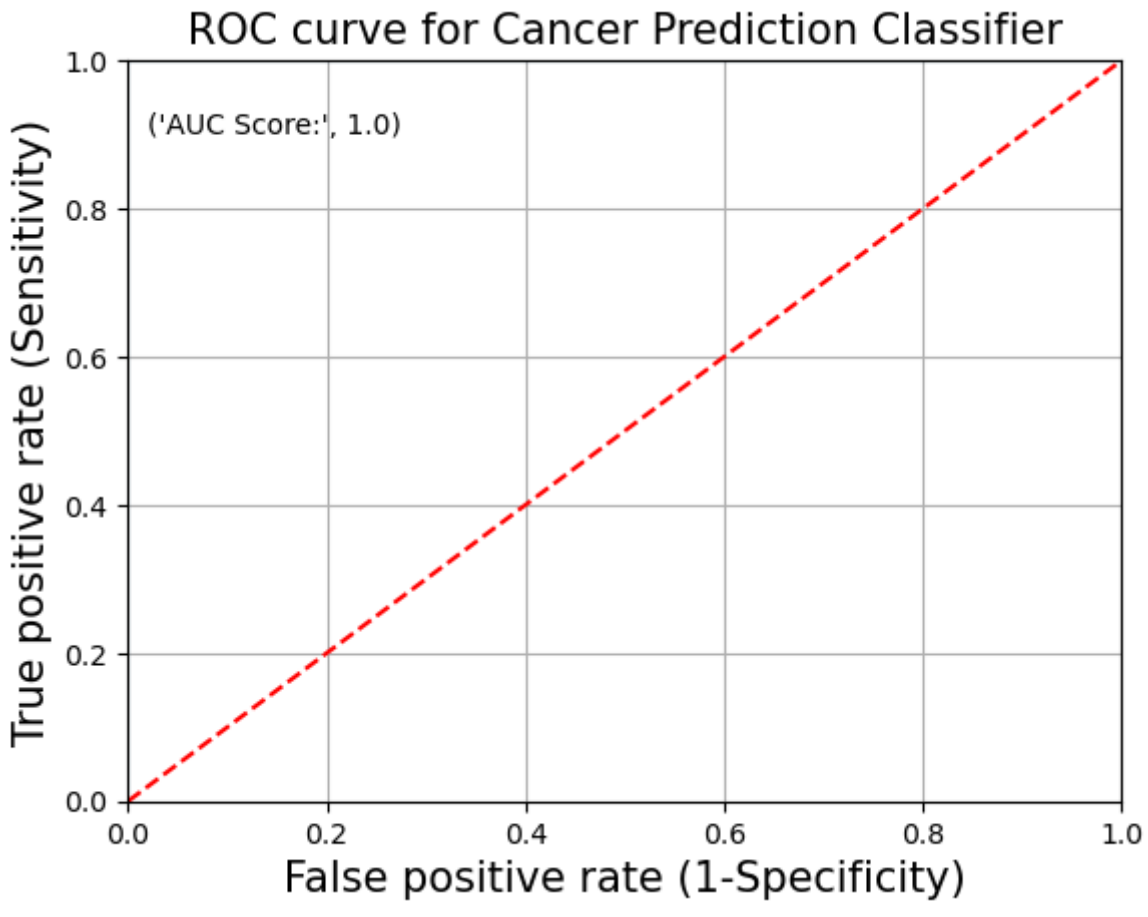
Interpretation: From the above output, we can see that there is a difference between the train and test accuracy; thus, we can conclude that the decision tree is over-fitted on the train data.

if we tune the hyperparameters in the decision tree, it helps to avoid the over-fitting of the tree.

In [232]:
```
plot_confusion_matrix(decision_tree, test_data = X_test)
```



In [233]:
```
plot_roc(decision_tree, test_data=X_test)
```



In [234]:
```
dt_model = DecisionTreeClassifier(criterion = 'gini',
                                  max_depth = 5,
                                  min_samples_split = 4,
                                  max_leaf_nodes = 6,
                                  random_state = 10)
decision_tree = dt_model.fit(X_train, y_train)
train_report = get_train_report(decision_tree, train_data=X_train)
print('Train data:\n', train_report)
test_report = get_test_report(decision_tree, test_data=X_test)
print('Test data:\n', test_report)
```

```
Train data:
               precision    recall  f1-score   support

         0.0       0.96      0.94      0.95      2932
         1.0       0.94      0.96      0.95      2754

    accuracy                           0.95      5686
   macro avg       0.95      0.95      0.95      5686
weighted avg       0.95      0.95      0.95      5686

Test data:
               precision    recall  f1-score   support

         0.0       0.96      0.94      0.95      1276
         1.0       0.94      0.96      0.95      1162

    accuracy                           0.95      2438
   macro avg       0.95      0.95      0.95      2438
weighted avg       0.95      0.95      0.95      2438
```

Interpretation: From the above output, we can see that there is slight significant difference between the train and test accuracy; thus, we can conclude that the decision tree is less over-fiited after specifying some of the hyperparameters.

Decision Tree Classification GridSearchCV

In [235]:
```
# tuned_paramaters = [{'criterion': ['entropy', 'gini'],
#                      'max_depth': range(2, 10),
#                      'max_features': ["sqrt", "log2"],
#                      'min_samples_split': range(2,10),
#                      'min_samples_leaf': range(1,10),
#                      'max_leaf_nodes': range(1, 10)}]
# decision_tree_classification = DecisionTreeClassifier(random_state = 10)
# tree_grid = GridSearchCV(estimator = decision_tree_classification,
#                          param_grid = tuned_paramaters,
#                          cv = 5)
# tree_grid_model = tree_grid.fit(X_train, y_train)
# print('Best parameters for decision tree classifier: ', tree_grid_model.best_params_, '\n')
```

In [236]:
```
# dt_model = DecisionTreeClassifier(criterion = tree_grid_model.best_params_.get('criterion'),
#                                   max_depth = tree_grid_model.best_params_.get('max_depth'),
#                                   max_features = tree_grid_model.best_params_.get('max_features'),
#                                   max_leaf_nodes = tree_grid_model.best_params_.get('max_leaf_nodes'),
#                                   min_samples_leaf = tree_grid_model.best_params_.get('min_samples_leaf'),
#                                   min_samples_split = tree_grid_model.best_params_.get('min_samples_split'),
#                                   random_state = 10)

# # use fit() to fit the model on the train set
# dt_model = dt_model.fit(X_train, y_train)
```

In [237]:
```
# print('Classification Report for train set: \n', get_train_report(dt_model, train_data = X_train))
```

In [238]:
```
# print('Classification Report for test set: \n', get_test_report(dt_model, test_data = X_test))
```

Interpretation: From the above output, we can see that there is no significant difference between the train and test accuracy; thus, we can conclude that the decision tree after tuning the hyperparameters avoids the over-fitting of the data.

Random Forest classification

In [239]:
```
rf_classification = RandomForestClassifier(n_estimators = 10, random_state = 10)
rf_model = rf_classification.fit(X_train, y_train)
```

In [240]:
```
train_report = get_train_report(rf_model,train_data = X_train)
print(train_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2932
         1.0       1.00      1.00      1.00      2754

    accuracy                           1.00      5686
   macro avg       1.00      1.00      1.00      5686
weighted avg       1.00      1.00      1.00      5686
```

In [241]:
```
test_report = get_test_report(rf_model, test_data = X_test)
print(test_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      1276
         1.0       1.00      1.00      1.00      1162

    accuracy                           1.00      2438
   macro avg       1.00      1.00      1.00      2438
weighted avg       1.00      1.00      1.00      2438
```

Random Forest Classification Grid Search CV

In [242]:
```
# tuned_paramaters_rf = [{'criterion': ['entropy', 'gini'],
#                         'n_estimators': [10, 30, 50, 70, 90],
#                         'max_depth': [10, 15, 20],
#                         'max_features': ['sqrt', 'log2'],
#                         'min_samples_split': [2, 5, 8, 11],
#                         'min_samples_leaf': [1, 5, 9],
#                         'max_leaf_nodes': [2, 5, 8, 11]}]

# # instantiate the 'RandomForestClassifier'
# # pass the 'random_state' to obtain the same samples for each time you run the code
# random_forest_classification = RandomForestClassifier(random_state = 10)

# # use GridSearchCV() to find the optimal value of the hyperparameters
# # estimator: pass the random forest classifier model
# # param_grid: pass the list 'tuned_parameters'
# # cv: number of folds in k-fold i.e. here cv = 5
# rf_grid = GridSearchCV(estimator = random_forest_classification,
#                        param_grid = tuned_paramaters_rf,
#                        cv = 5)

# # use fit() to fit the model on the train set
# rf_grid_model = rf_grid.fit(X_train, y_train)

# # get the best parameters
# print('Best parameters for random forest classifier: ', rf_grid_model.best_params_, '\n')
```

In [243]:
```
# rf_model = RandomForestClassifier(criterion = rf_grid_model.best_params_.get('criterion'),
#                                   n_estimators = rf_grid_model.best_params_.get('n_estimators'),
#                                   max_depth = rf_grid_model.best_params_.get('max_depth'),
#                                   max_features = rf_grid_model.best_params_.get('max_features'),
#                                   max_leaf_nodes = rf_grid_model.best_params_.get('max_leaf_nodes'),
#                                   min_samples_leaf = rf_grid_model.best_params_.get('min_samples_leaf'),
#                                   min_samples_split = rf_grid_model.best_params_.get('min_samples_split'),
#                                   random_state = 10)
# rf_model = rf_model.fit(X_train, y_train)
# print('Classification Report for test set:\n', get_test_report(rf_model,test_data = X_test))
```

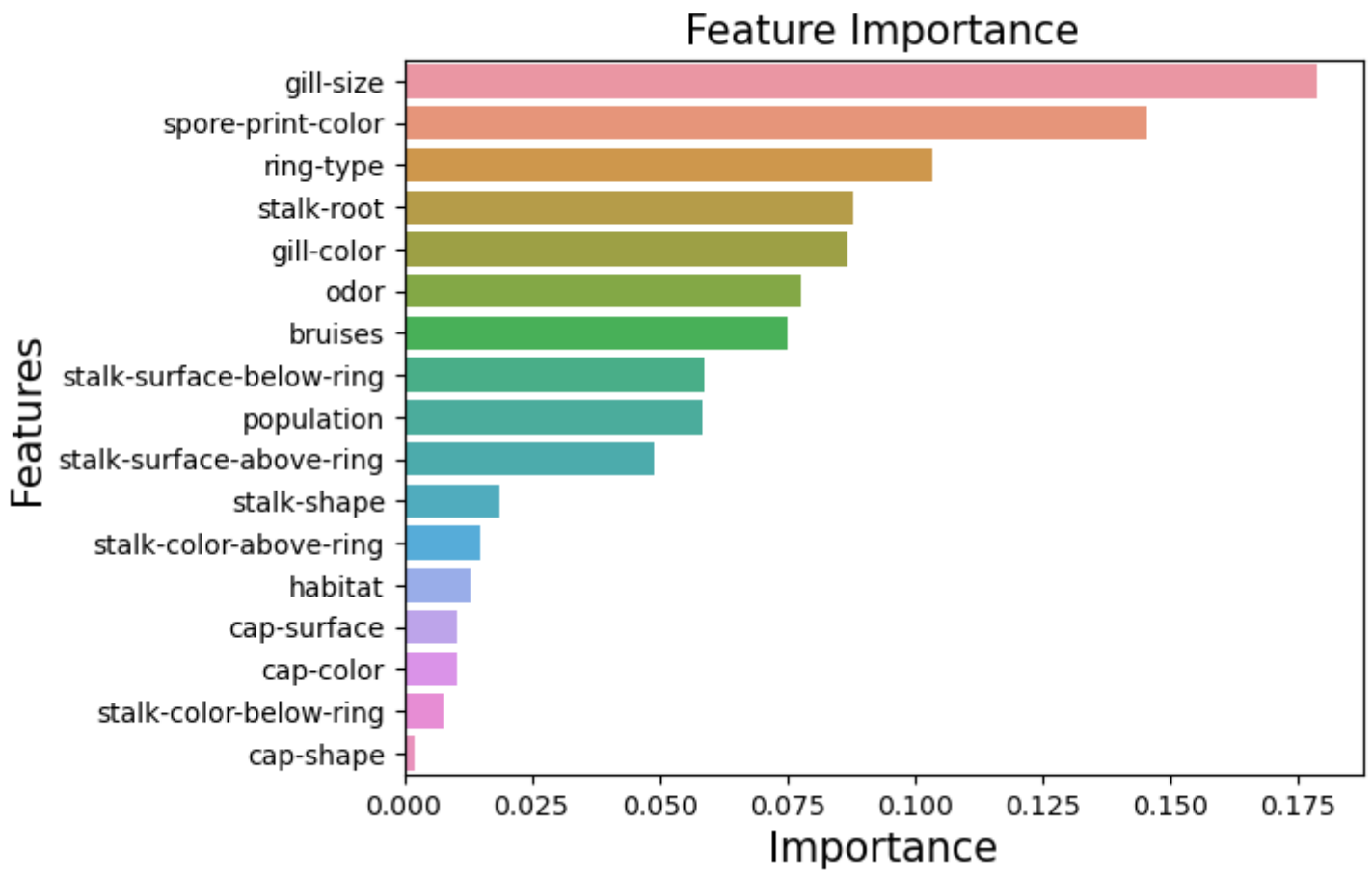
In [244]:
```
# print('Classification Report for Train set:\n', get_train_report(rf_model,train_data = X_train))
```

In [245]:
```
# plot_roc(rf_model,test_data=X_test)
```

In [246]:
```
# plot_confusion_matrix(rf_model, test_data=X_test)
```

Interpretation: The accuracy of the test dataset increased from 0.81 to 0.82 after tuning of the hyperparameters. Also, the sensitivity and specificity of the model are balanced.

In [247]:
```
important_features = pd.DataFrame({'Features': X_train.columns,
                                   'Importance': rf_model.feature_importances_})
important_features = important_features.sort_values('Importance', ascending = False)
sns.barplot(x = 'Importance', y = 'Features', data = important_features)
plt.title('Feature Importance', fontsize = 15)
plt.xlabel('Importance', fontsize = 15)
plt.ylabel('Features', fontsize = 15)
plt.show()
```



In [ ]:
```
```

Ada Boost

In [248]:
```
ada_model = AdaBoostClassifier(n_estimators = 40, random_state = 10)
ada_model.fit(X_train, y_train)
```

Out[248]:
```
AdaBoostClassifier(n_estimators=40, random_state=10)
```

In [249]:
```
test_report = get_train_report(ada_model,train_data = X_train)
print(test_report)
```

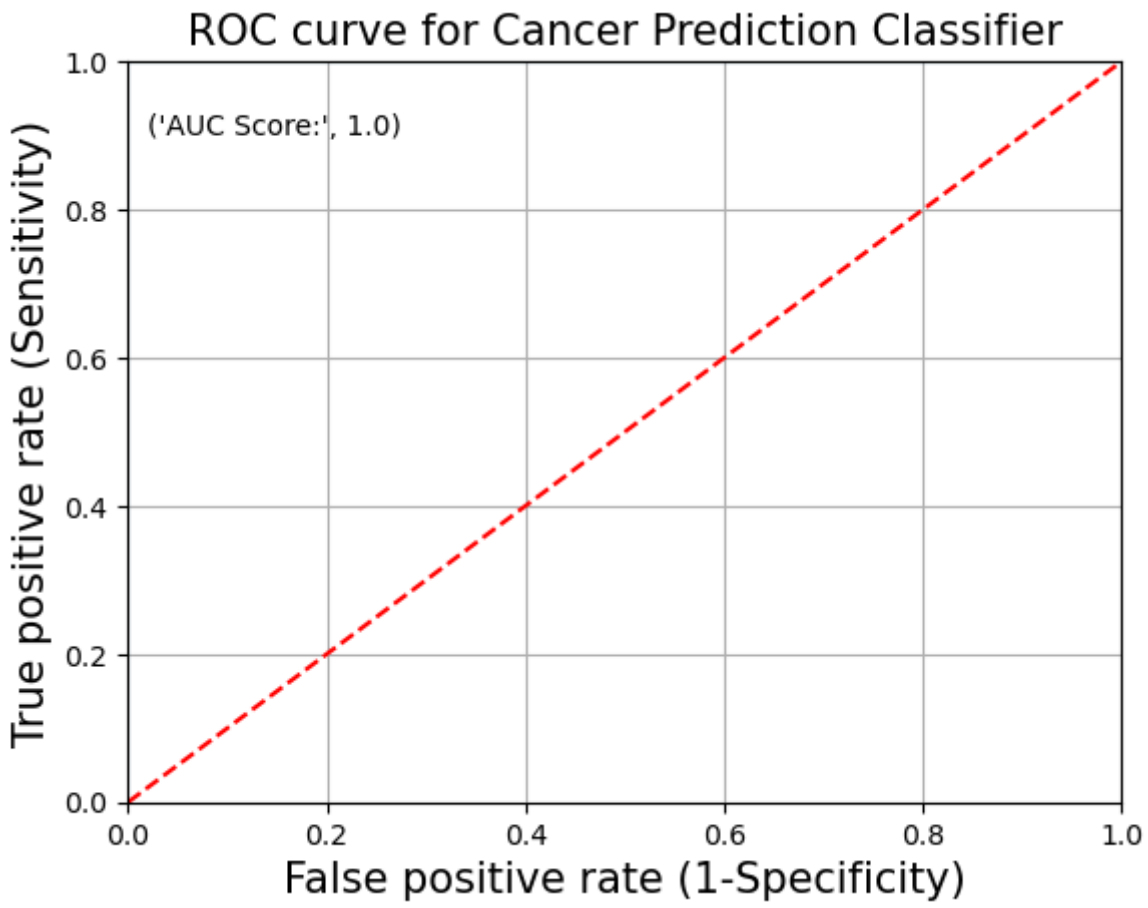
```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2932
         1.0       1.00      1.00      1.00      2754

    accuracy                           1.00      5686
   macro avg       1.00      1.00      1.00      5686
weighted avg       1.00      1.00      1.00      5686
```

In [250]:
```
test_report = get_test_report(ada_model,test_data = X_test)
print(test_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      1276
         1.0       1.00      1.00      1.00      1162

    accuracy                           1.00      2438
   macro avg       1.00      1.00      1.00      2438
weighted avg       1.00      1.00      1.00      2438
```

Interpretation: The output shows that the model is 83% accurate.

In [251]:
```
plot_roc(ada_model,test_data=X_test)
```



Gradient Boosting Classification

In [252]:
```
gboost_model = GradientBoostingClassifier(n_estimators = 150, max_depth = 10, random_state = 10)
gboost_model.fit(X_train, y_train)
```

Out[252]:
```
GradientBoostingClassifier(max_depth=10, n_estimators=150, random_state=10)
```

In [253]:
```
test_report = get_train_report(gboost_model,train_data = X_train)
print(test_report)
```

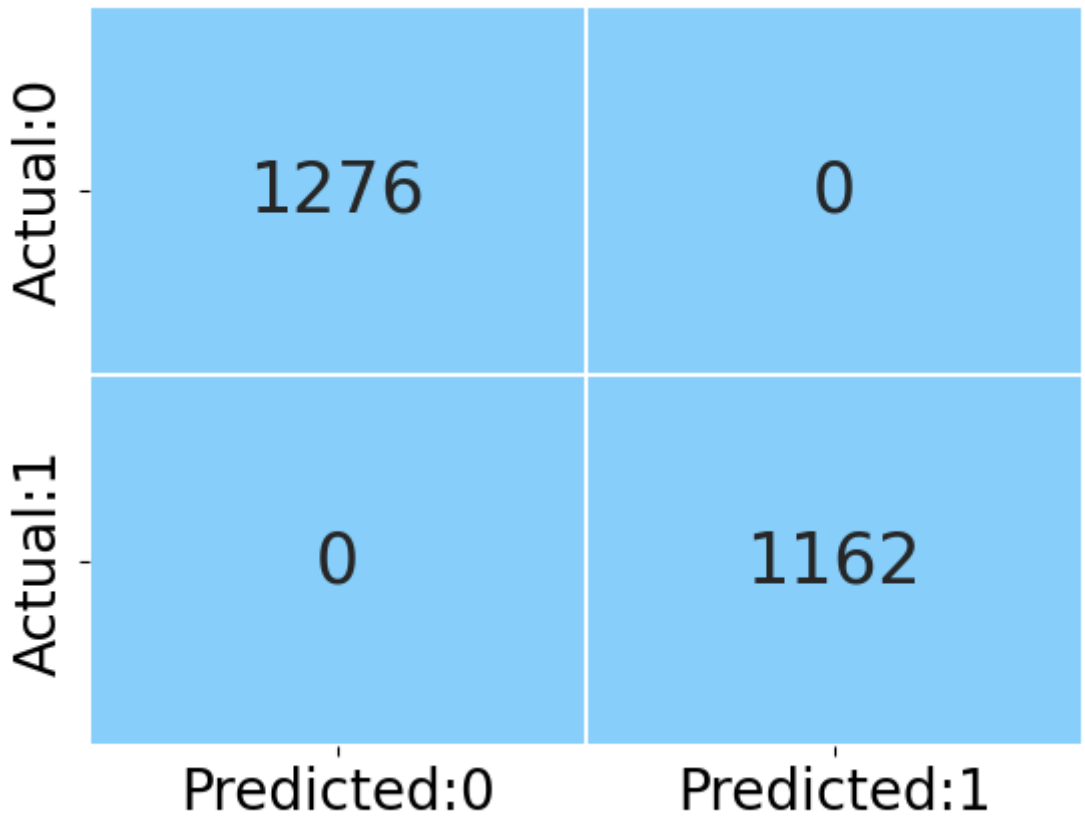
```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2932
         1.0       1.00      1.00      1.00      2754

    accuracy                           1.00      5686
   macro avg       1.00      1.00      1.00      5686
weighted avg       1.00      1.00      1.00      5686
```

In [254]:
```
test_report = get_test_report(gboost_model,test_data = X_test)
print(test_report)
```

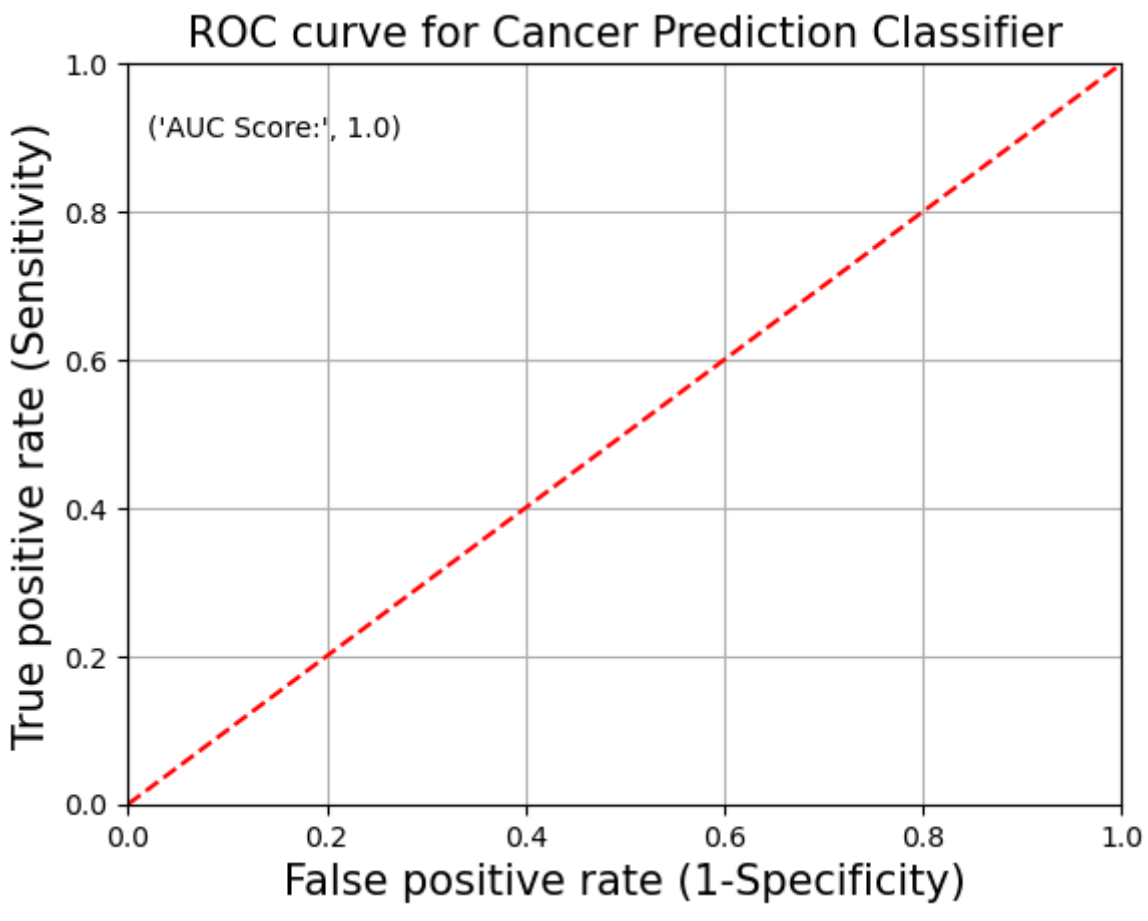
```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      1276
         1.0       1.00      1.00      1.00      1162

    accuracy                           1.00      2438
   macro avg       1.00      1.00      1.00      2438
weighted avg       1.00      1.00      1.00      2438
```

In [ ]:
```

```

In [255]:
```
plot_confusion_matrix(gboost_model, test_data=X_test)
```



In [256]:
```
plot_roc(gboost_model,test_data = X_test)
```



XGB Classification

In [257]:
```
xgb_model = XGBClassifier(max_depth = 10, gamma = 1)
xgb_model.fit(X_train, y_train)
```

Out[257]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=1, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=10, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

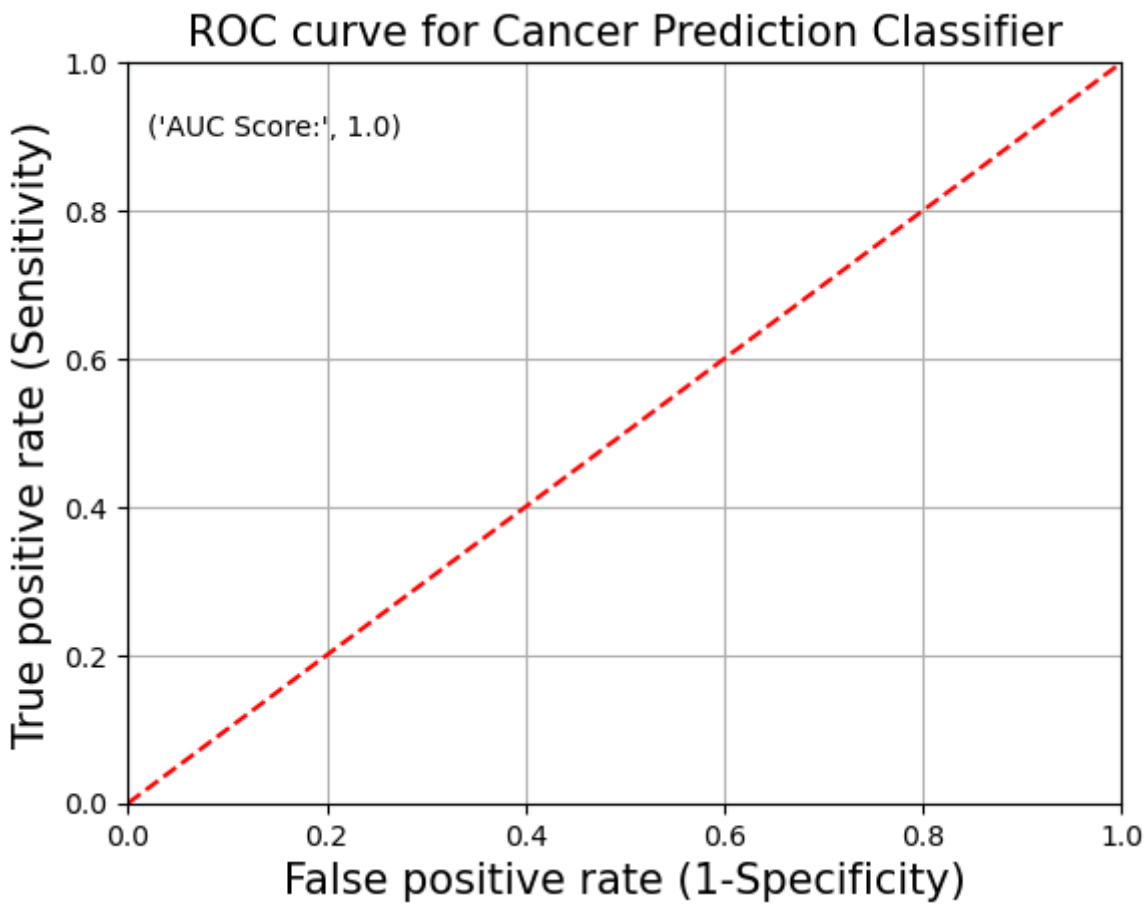
In [258]:
```
test_report = get_train_report(xgb_model,train_data = X_train)
print(test_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2932
         1.0       1.00      1.00      1.00      2754

    accuracy                           1.00      5686
   macro avg       1.00      1.00      1.00      5686
weighted avg       1.00      1.00      1.00      5686
```

In [259]:
```
test_report = get_test_report(xgb_model,test_data = X_test)
print(test_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      1276
         1.0       1.00      1.00      1.00      1162

    accuracy                           1.00      2438
   macro avg       1.00      1.00      1.00      2438
weighted avg       1.00      1.00      1.00      2438
```

In [260]:
```
plot_roc(xgb_model,test_data = X_test)
```



XGB Classification Grid Search CV

In [261]:
```
tuning_parameters = {'learning_rate': [0.1, 0.2, 0.3, 0.4, 0.5, 0.6],
                     'max_depth': range(3,10),
                     'gamma': [0, 1, 2, 3, 4]}
xgb_model = XGBClassifier()
xgb_grid = GridSearchCV(estimator = xgb_model, param_grid = tuning_parameters, cv = 3, scoring = 'roc_auc')
xgb_grid.fit(X_train, y_train)
print('Best parameters for XGBoost classifier: ', xgb_grid.best_params_, '\n')
```

```
Best parameters for XGBoost classifier:  {'gamma': 0, 'learning_rate': 0.1, 'max_depth': 3}
```

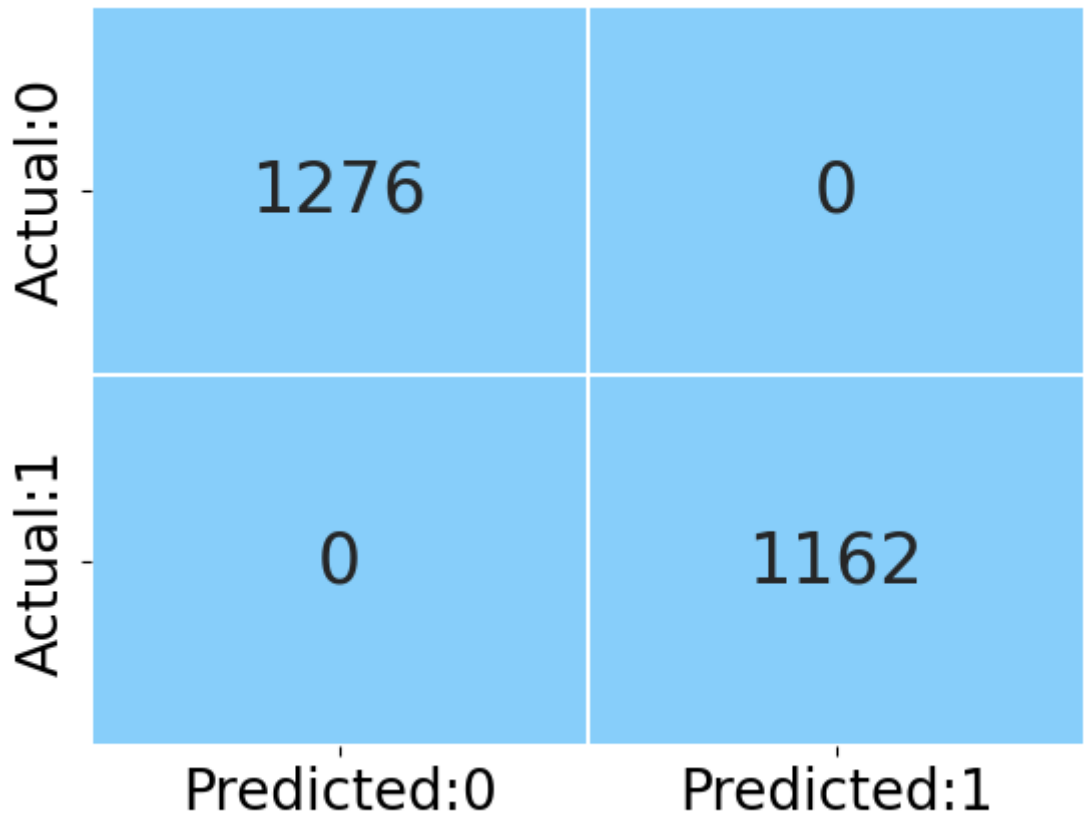
In [262]:
```
xgb_grid_model = XGBClassifier(learning_rate = xgb_grid.best_params_.get('learning_rate'),
                               max_depth = xgb_grid.best_params_.get('max_depth'),
                              gamma = xgb_grid.best_params_.get('gamma'))
xgb_model = xgb_grid_model.fit(X_train, y_train)
print('Classification Report for test set:\n', get_test_report(xgb_model,test_data = X_test))
```

```
Classification Report for test set:
               precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      1276
         1.0       1.00      1.00      1.00      1162

    accuracy                           1.00      2438
   macro avg       1.00      1.00      1.00      2438
weighted avg       1.00      1.00      1.00      2438
```

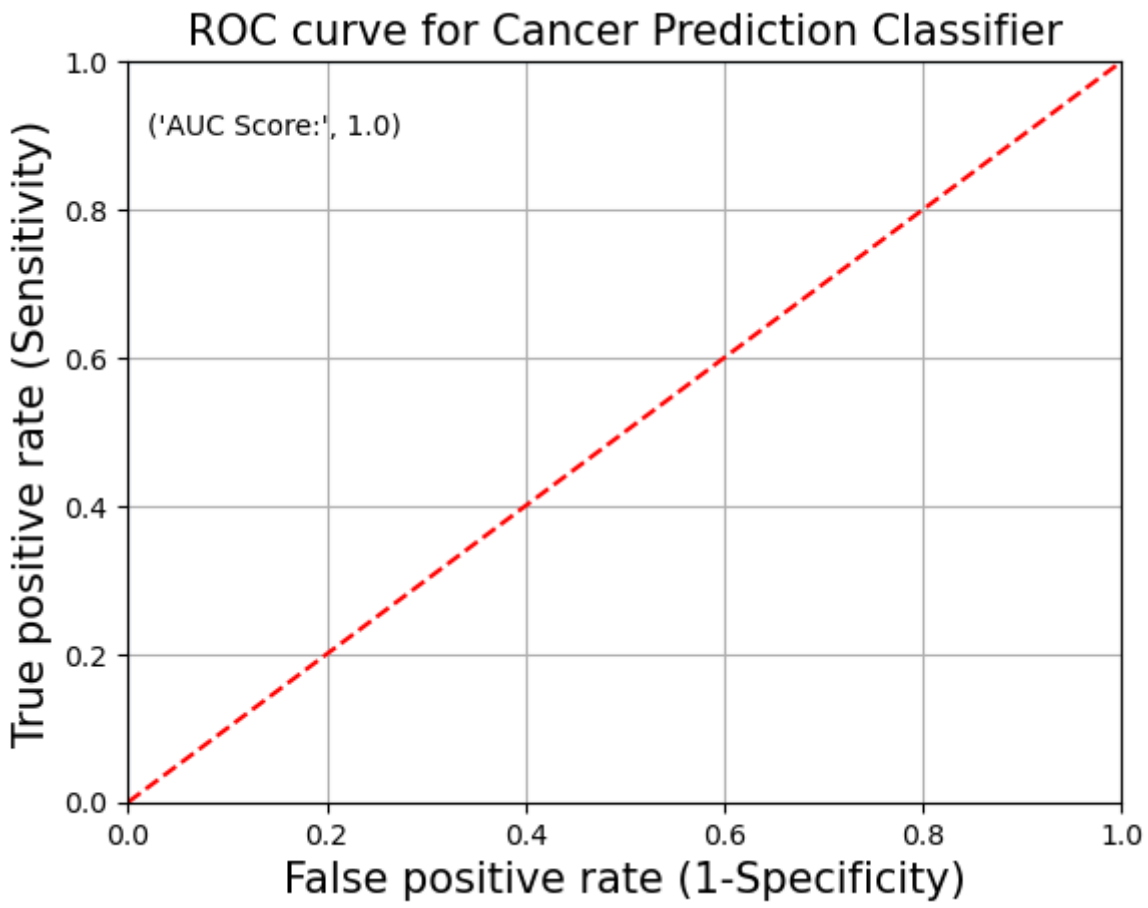
In [263]:
```
print('Classification Report for Train set:\n', get_train_report(xgb_model,train_data = X_train))
```

```
Classification Report for Train set:
               precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2932
         1.0       1.00      1.00      1.00      2754

    accuracy                           1.00      5686
   macro avg       1.00      1.00      1.00      5686
weighted avg       1.00      1.00      1.00      5686
```

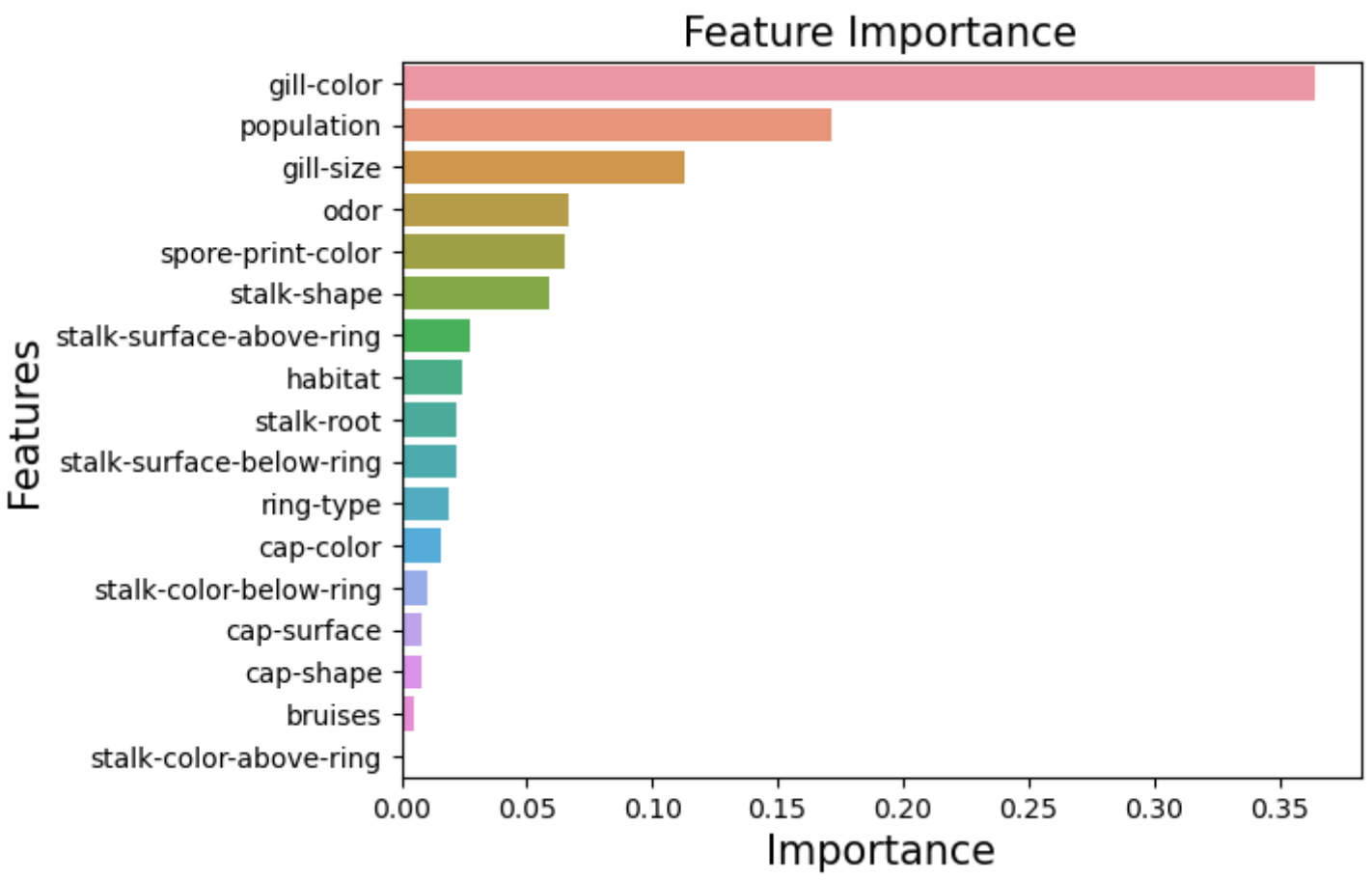
In [264]:
```
plot_confusion_matrix(xgb_grid_model, test_data=X_test)
```



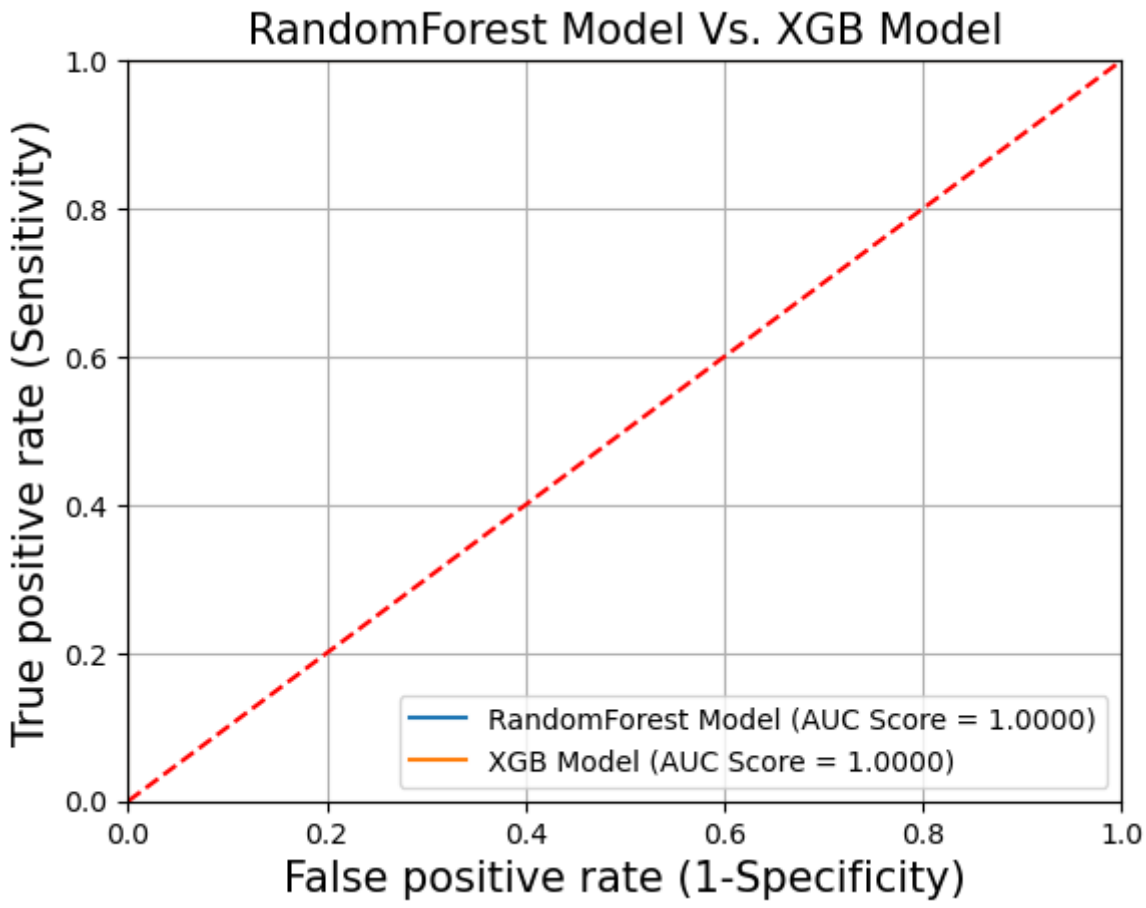
In [265]:
```
plot_roc(xgb_model,test_data = X_test)
```



In [266]:
```
important_features = pd.DataFrame({'Features': X_train.columns,
                                   'Importance': xgb_model.feature_importances_})
important_features = important_features.sort_values('Importance', ascending = False)
sns.barplot(x = 'Importance', y = 'Features', data = important_features)
plt.title('Feature Importance', fontsize = 15)
plt.xlabel('Importance', fontsize = 15)
plt.ylabel('Features', fontsize = 15)
plt.show()
```



In [267]:
```
y_pred_prob_rf = rf_model.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob_rf)
auc_score_rf = roc_auc_score(y_test, y_pred_prob_rf)
plt.plot(fpr, tpr, label='RandomForest Model (AUC Score = %0.4f)' % auc_score_rf)
y_pred_prob_xgb = xgb_grid_model.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob_xgb)
auc_score_xgb = roc_auc_score(y_test, y_pred_prob_xgb)
plt.plot(fpr, tpr, label='XGB Model (AUC Score = %0.4f)' % auc_score_xgb)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.plot([0, 1], [0, 1],'r--')
plt.title('RandomForest Model Vs. XGB Model', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)
plt.legend(loc = 'lower right')
plt.grid(True)
```



Stacking Classification

In [268]:
```
# consider the various algorithms as base learners
base_learners = [('rf_model', RandomForestClassifier(criterion = 'entropy', max_depth = 10, max_features = 'sqrt',
                                                     max_leaf_nodes = 8, min_samples_leaf = 5, min_samples_split = 2,
                                                     n_estimators = 50, random_state = 10)),
                 ('KNN_model', KNeighborsClassifier(n_neighbors = 17, metric = 'euclidean')),
                 ('NB_model', GaussianNB())]

# initialize stacking classifier
# pass the base learners to the parameter, 'estimators'
# pass the Naive Bayes model as the 'final_estimator'/ meta model
stack_model = StackingClassifier(estimators = base_learners, final_estimator = GaussianNB())

# fit the model on train dataset
stack_model.fit(X_train, y_train)
```

Out[268]:
```
StackingClassifier(estimators=[('rf_model',
                                RandomForestClassifier(criterion='entropy',
                                                       max_depth=10,
                                                       max_features='sqrt',
                                                       max_leaf_nodes=8,
                                                       min_samples_leaf=5,
                                                       n_estimators=50,
                                                       random_state=10)),
                               ('KNN_model',
                                KNeighborsClassifier(metric='euclidean',
                                                     n_neighbors=17)),
                               ('NB_model', GaussianNB())],
                   final_estimator=GaussianNB())
```

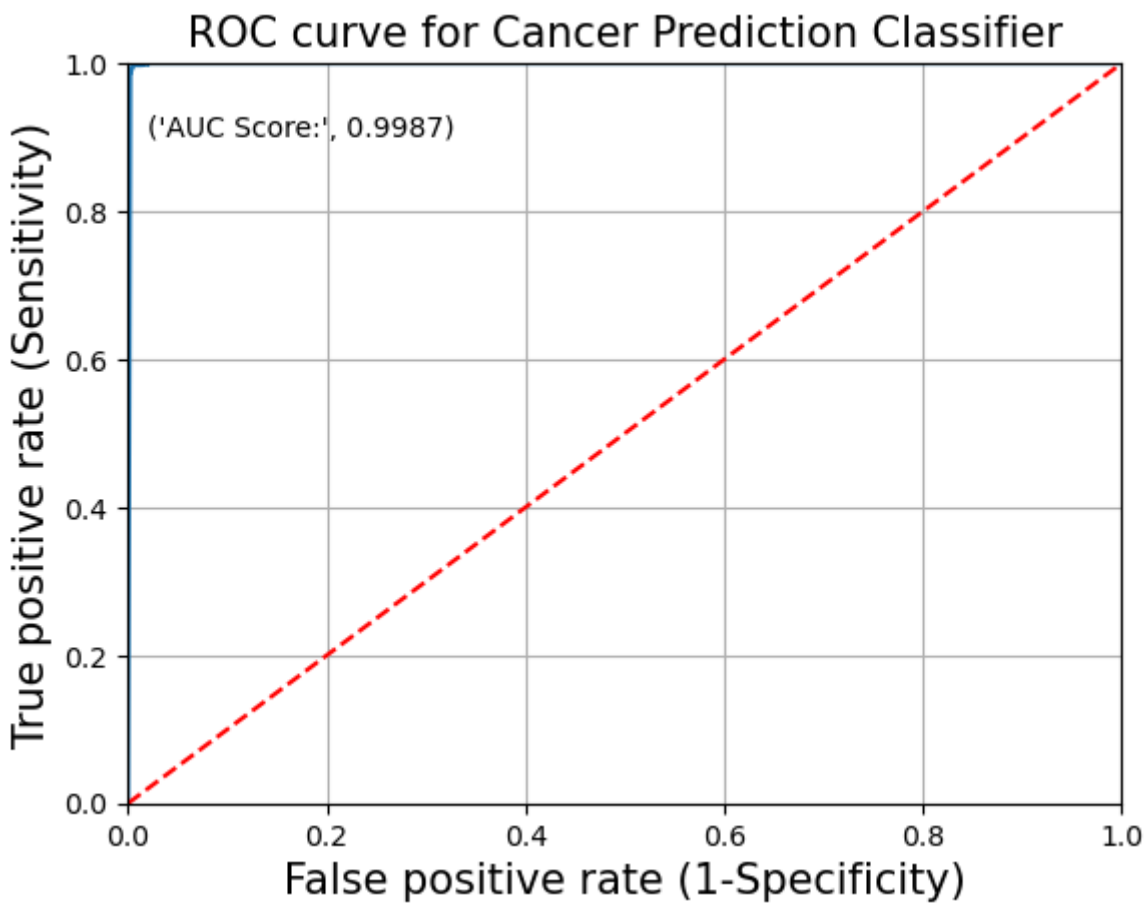
In [269]:
```
test_report = get_train_report(stack_model,train_data = X_train)
print(test_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2932
         1.0       1.00      1.00      1.00      2754

    accuracy                           1.00      5686
   macro avg       1.00      1.00      1.00      5686
weighted avg       1.00      1.00      1.00      5686
```

In [270]:
```
test_report = get_test_report(stack_model,test_data = X_test)
print(test_report)
```

```
              precision    recall  f1-score   support

         0.0       1.00      0.99      1.00      1276
         1.0       0.99      1.00      1.00      1162

    accuracy                           1.00      2438
   macro avg       1.00      1.00      1.00      2438
weighted avg       1.00      1.00      1.00      2438
```

In [271]:
```
plot_roc(stack_model,test_data = X_test)
```



In [ ]: